International Business & Economics Studies
ISSN 2640-9852 (Print) ISSN 2640-9860 (Online)
Vol. 8, No. 4, 2026
www.scholink.org/ojs/index.php/ibes

Original Paper

Artificial Intelligence, Task Displacement and the Labor Income Share: A Theoretical Analysis Based on the Task Framework

Beibei Yang[1]

[1] Guangxi Normal University, Guilin, Guangxi, China

Received: September 27, 2026 Accepted: October 29, 2026 Online Published: November 18, 2026

doi:10.22158/ibes.v8n4p205 URL: http://dx.doi.org/10.22158/ibes.v8n4p205

Abstract

Artificial intelligence is progressively reassigning production tasks from labor to capital, and the consequences for the labor income share lie at the centre of current research on macroeconomic distribution. This paper builds a static task-based model with a continuum of tasks and derives a closed-form solution for the labor income share in terms of three dimensions that are in principle observable: the breadth of automation, efficiency-adjusted capital intensity, and the elasticity of substitution across tasks. Four propositions follow. Holding capital intensity fixed, a greater breadth of automation always lowers the labor income share, with an elasticity depending only on the share itself and on the substitution elasticity; the direction of the effect of capital intensity is signed by that elasticity; and new task creation operates in the opposite direction, with an elasticity exactly (1+a) times that of displacement. Combining the three yields a condition that can be checked term by term for a stable labor share. Applied to China, the framework accounts for the decline, trough and stabilization of the share, and identifies the extension of automation to routine cognitive tasks as a potential break in that balance.

Keywords

artificial intelligence, task displacement, labor income share, new task creation, macroeconomic distribution

1. Introduction

Artificial intelligence is a central driver of the current technological wave. What sets it apart from the steam engine, electrification and information technology is that it operates on tasks rather than on industries: it creates no new sectors but takes over, one by one, the production steps previously performed by labor. Its effect is in this sense purely distributional, raising productive efficiency while redrawing the boundary between capital and labor within existing processes.

The labor income share is the aggregate indicator of where that boundary lies, and its movements bear directly on household income, consumption demand and the composition of domestic demand. A sustained decline has been documented across the major economies since the 1980s [1], and China experienced a larger one after the mid-1990s [2,3]. Equally notable, the Chinese decline bottomed out between 2007 and 2011, then stabilized and began a slow recovery [4], whereas the downward trend in the United States has not visibly reversed. Why should one technological wave leave such different distributional traces in two economies?

A word on measurement is needed, because the fact recurs below. The year of the trough varies with the data source and accounting convention: on the income approach to GDP, the compensation of employees fell to about 40 percent around 2007 and has recovered to roughly 45 percent, whereas the flow-of-funds accounts date the recovery from about 2011 at a markedly higher level, and separating the employee from the self-employed economy shifts the level again [5]. All measures agree that a decline lasting more than a decade ended around 2010. The argument below uses only that common conclusion where direction is at issue, and names the convention only where levels matter.

The answer depends on how artificial intelligence is understood to bear on distribution. Treated as capital-augmenting technical change, its effect is governed entirely by the elasticity of substitution between capital and labor [6], which cannot account for the divergence between the two economies. Treated as synonymous with automation, it must depress the labor share [7], which conflicts with the Chinese stabilization after 2007. Both readings omit a dimension that matters: artificial intelligence displaces existing tasks and simultaneously creates the conditions for new ones, and which runs faster determines the outcome.

The central claim of this paper is that the trajectory of the labor income share depends not on whether artificial intelligence displaces labor but on the relative magnitude of the breadth of automation and the speed of task creation. To turn this intuition into propositions that can be examined, the paper builds a task-based model with a continuum of tasks and decomposes the influence of artificial intelligence into three dimensions that are in principle observable: the breadth of automation a, the ratio of automated tasks to tasks performed by labor; efficiency-adjusted capital intensity κ; and the elasticity of substitution across tasks σ. The labor income share then admits a closed form:

$$S_L=\frac{1}{1+\kappa^{(\sigma-1)/\sigma}a^{1/\sigma}}$$

Four propositions follow. First, a greater breadth of automation always lowers the labor income share, with an elasticity independent of the substitution elasticity, so the claim that machines necessarily depress the labor share is robust along the extensive margin. Second, the effect of efficiency-adjusted capital intensity is negative when $\sigma>1$, positive when and zero when $\sigma=1$, which explains why accumulation of equal strength leaves different traces in different economies. Third, new task creation raises the share by lowering the breadth of automation, with an elasticity of the opposite sign, the same form, and exactly times the magnitude. Fourth, the three together give a necessary and sufficient

condition for a constant share: the growth rate of labor tasks must equal that of automated tasks plus times the rate of efficiency-adjusted capital deepening — the theoretical result and the key to the Chinese experience below.

The paper's relation to the existing task framework should be stated plainly. The canonical statement of that framework already carries factor shares in its title [7]: its static model already delivers the directional results that automation lowers the labor share and that new task creation raises it, and already collapses, when the substitution elasticity equals one, to the Cobb–Douglas form in which the share equals the fraction of tasks not automated. This paper does not claim to have discovered that relationship, nor does it suppose that earlier work was concerned with employment alone.

The contribution lies elsewhere, in three respects. In exposition, the paper gives a closed form in terms of the breadth of automation, efficiency-adjusted capital intensity and the elasticity of substitution, and writes the displacement and creation elasticities out explicitly: opposite signs, the same functional form, magnitudes differing by the factor $(1+a)$. Earlier work states its results as a sign or a numerical comparative static; the expression here lets the relative strength of the two forces be read off term by term. In mechanism, the three dimensions become a stability condition of the accounting-identity kind, decomposing the movement of the share into the gap between the growth rates of labor and automated tasks and singling out the breadth of automation, rather than capital deepening, as the variable organizing the Chinese sequence. In application, the condition assesses the distributional consequences of generative artificial intelligence and argues that what preserves the labor share now is not the restraint of automation but the pace of new task creation — a conclusion running against the counsel to slow the technology down.

The remainder is organized as follows. Section 2 reviews the literature and locates the paper within it; Section 3 sets out the baseline model, derives the closed-form solution and establishes the four propositions; Section 4 relaxes the baseline assumptions, endogenizes the automation boundary and conducts a scenario analysis; Section 5 applies the framework to China and draws out the policy implications; Section 6 concludes.

2. Literature Review

Four strands bear on this paper: the older work on technical change and factor shares, the task-based approach, the empirical literature on the distributional effects of artificial intelligence, and the literature on the labor income share in China. They are taken in turn.

2.1 Induced Innovation and Biased Technical Change

The question of how technical change affects factor income shares is an old one. The induced-innovation hypothesis gave the first answer: changes in relative factor prices direct innovation toward economizing on the factor that has become expensive, so that rising wages elicit labor-saving technology [8]. The idea was carried forward in the growth and distribution theory that followed [9,10], but technical change was long treated as neutral and income shares as constants, which is one of the

Kaldor stylized facts.

That treatment was broken by the theory of biased technical change, which distinguished factor-augmenting from factor-biased technical change, made the direction of technical change endogenous and traced it to relative-price and market-size effects, and showed that when the elasticity of substitution differs from one, movements in the labor income share can be accounted for entirely by capital-augmenting technical change [6,11]. The labor income share is therefore not a constant but a function of the direction of technology and of the elasticity of substitution.

Applied to the global decline, capital deepening driven by falling investment-goods prices is identified as the main cause [1]. The explanation runs into a difficulty: if capital and labor are substitutes, capital deepening should depress the labor share, yet a substantial body of estimates places the Chinese capital–labor elasticity below one, in which case it should raise it. The elasticity of substitution across tasks, σ, is not the same object as the factor elasticity: the former describes substitutability among tasks, whereas the latter is endogenous, determined by the structure of tasks and the allocation of factors, and the two cannot be converted into one another. A factor-substitution account alone is therefore incomplete, and the way technology enters production needs to be specified.

2.2 The Task-based Approach

The task-based approach offers an alternative. Its starting point is that technology does not displace labor as a whole but particular tasks performed by labor, so the distributional consequences of a technology shock depend on how codifiable those tasks are [12]. Task assignment was subsequently endogenized, with skill supply, technical change and trade jointly determining the allocation of labor across tasks [13].

The approach was then formalized as a tractable general-equilibrium model in which production is a continuum of tasks and technology operates through the movement of an automation boundary (displacement) and the extension of the task space (creation). Its static part establishes that automation lowers the labor share, that new task creation raises it, and that in the Cobb–Douglas limit the share equals the fraction of tasks not automated [7], replacing a question with no general answer by a conditional proposition. Subsequent extensions show that the productivity effect of automation raises demand for non-automated tasks and partly offsets displacement [14], while evidence from US commuting zones finds negative effects of robot adoption on employment and wages [15].

This paper builds directly on that framework; the difference lies less in the object of study than in the form of expression and its use. That literature delivers sign propositions, or comparative statics that must await the general equilibrium before they can be signed. The present paper writes the share in closed form and compresses the contest between displacement and creation into an explicit condition on the breadth of automation and efficiency-adjusted capital intensity κ, so that the relative strength of the two forces can be compared term by term and put to work in interpreting particular episodes.

2.3 The Distributional Effects of Artificial Intelligence

Empirical work on the distributional consequences of artificial intelligence has grown rapidly. Using

industry data for seventeen countries, one study finds that robot use raises labor productivity, has an effect on aggregate employment close to zero, and depresses the relative wages of low-skilled workers [16]. Theoretical work emphasizes the plasticity of the direction of technology, that is, that its distributional consequences depend on where the technology is pushed [17]. Evidence from worldwide industrial robot data indicates pronounced heterogeneity in the effect on inclusive growth [18]. Measurements of the Chinese factor income distribution from the standpoint of biased technical change identify that bias as an important explanation for the declining labor share [19].

On the theoretical side, a multi-sector dynamic general-equilibrium analysis shows that an increase in artificial intelligence services, or in intelligence-augmenting technology, reallocates factors across sectors according to sectoral differences in intelligence output elasticities and elasticities of substitution, and that this structural transformation in turn moves the labor income share [20]. A skill-bias perspective yields a similar conclusion in theory and evidence [21]. Introducing skill heterogeneity into a model of endogenous technical change, new task creation raises the demand for low-skilled labor and lowers the skill premium in the long run [22].

Measuring at the level of the task provides another route to the net effect. Estimating the cost savings that artificial intelligence generates task by task and weighting them by the share of tasks affected places an upper bound on the gain in aggregate total factor productivity: no more than 0.66 percent over ten years, revised down to 0.53 percent once allowance is made for the tasks not yet displaced being harder to learn and more context-dependent. Even where artificial intelligence raises the productivity of low-skilled workers on some tasks without creating new tasks for them, inequality can still rise, and what widens is the gap between capital and labor income [23].

Micro evidence from China is less settled, the disagreement turning on whether displacement or creation is the stronger force. Using intelligent-manufacturing pilots as a quasi-natural experiment, one study finds that human-capital upgrading induced by complementarity dominates, so that the labor income share of the affected firms rises [24]. An analysis of recruitment-platform big data finds that artificial intelligence reduces demand for routine occupations while significantly raising it for non-routine cognitive ones, in new as well as existing job categories [25]. A firm-level study incorporating both channels finds that displacement and extension both raise total factor productivity, but that the former lowers wages and the labor share while the latter raises both, and that within the sample period displacement outweighs extension [26]. A further strand starting from labor market power, with imperfect competition and skill heterogeneity in a multi-product firm framework, finds substantial monopsony power under which workers capture only 63 percent of the value they create; by expanding scale, extending the production boundary and raising product complexity, artificial intelligence reduces that power and improves the distribution between capital and labor [27].

This body of work has deepened understanding of the distributional consequences of artificial intelligence, yet leaves two problems unresolved. The first is that the divergence of conclusions owes much to differences in the level of observation and in the object identified: displacement dominates

within firms over the sample period, whereas the stabilization of the aggregate share may come from the diffusion of new tasks across sectors and the reallocation of labor. The two need not conflict, but the literature has yet to express their relative strength as comparable elasticities within a single framework. The second is that most studies treat artificial intelligence as a single shock and infer its net effect from a comparative static; even where displacement and creation are distinguished, analytic expressions in terms of automation breadth, capital intensity and substitution elasticity are rarely supplied. Conclusions are consequently hard to compare: two papers reporting a lower labor share may describe quite different mechanisms with quite different policy implications.

2.4 The Labor Income Share in China

Research on the Chinese labor income share has produced three broad explanations. The first is structural: the decline is attributed mainly to the rising weight of capital-intensive sectors during industrialization [2]. The second rests on factor-market distortions: the household registration system, financial repression and labor market segmentation depress labor compensation [3]. The third is technical bias: biased technical change is the deeper cause [19].

Each has empirical support, and each faces the same difficulty: none accounts for the turning point around 2007. If the decline came from structural transformation, the share should recover as services grow, and it has; if from technical bias, why did technology stop pressing the share down? The answer offered here is that after 2007 the forces restraining the breadth of automation strengthened appreciably: services extended the task space, the platform economy raised the relative efficiency of labor on existing tasks, and together they slowed the rise in and offset the negative effect of capital deepening. The account connects with the diagnosis of rising labor costs after the Lewis turning point [28] but emphasizes a different channel: rising wages do induce automation, yet they also expand demand for services and accelerate the creation of new tasks.

2.5 Assessment and Positioning

The literature thus supplies three foundations: the task framework, the language in which the distributional effects of artificial intelligence can be analyzed; the theory of biased technical change, the macro perspective on movements in the share; and the Chinese literature, a rich set of stylized facts. Three gaps remain. Analytic expressions for the labor income share mostly take the form of sign propositions or numerical comparative statics, and a unified closed form in terms of the breadth of automation, capital intensity and the substitution elasticity is rarely given, so the competing forces cannot be compared directly. The symmetry between the displacement and creation elasticities has not been written down explicitly, and no single framework accounts for the Chinese sequence of decline, trough and stabilization.

This paper attempts to advance on these three points. It is theoretical and contains no econometric test, for two reasons. At the level of data, the breadth of automation is not directly observed; the available proxies, such as robot density and patent counts, cover only the formal sector and cannot capture displacement at the level of the task. At the level of theory, the relative strength of displacement and

creation is precisely the kind of object that can be characterized cleanly, and whose conclusions are sensitive to parameter values. Clarifying the theoretical condition is therefore a precondition for the empirical work that should follow.

3. The Baseline Model

The model has three building blocks: a constant-elasticity technology defined over a continuum of tasks, a competitive allocation of factors across those tasks, and an automation boundary separating the tasks capital can perform from those only labor can perform. The solution for the labor income share follows directly, and the four propositions are comparative statics of that solution.

3.1 Production and Task Structure

Three assumptions about factor markets precede the formal setup. First, capital and labor are exogenous endowments fully employed in equilibrium. Second, factor markets are perfectly competitive, with no monopsony or monopoly power on either side. Third, capital and labor can be allocated freely across tasks. Together these imply that the model concerns relative factor rewards rather than employment: displacement appears as a reallocation of tasks, not as unemployment. The gain is that the analysis can concentrate on distribution; the cost is that the model cannot speak to the effect of artificial intelligence on total employment, nor to the role of market power. Both limitations return in the concluding section.

A single final good is produced from a continuum of tasks, indexed by $i \in [0,N]$, where is the upper bound of the task space and represents the total quantity of tasks in the economy. The production function takes the constant-elasticity-of-substitution form

$$Y=\left[\int_0^N y(i)^{\frac{\sigma-1}{\sigma}}\mathrm{d}i\right]^{\frac{\sigma}{\sigma-1}}, \qquad \sigma>0,\ \sigma\neq 1 \tag{1}$$

where is output of task and is the elasticity of substitution across tasks. A value of means that tasks are gross substitutes and that they are gross complements. It bears repeating that describes substitutability among tasks, not between factors; the latter is endogenous here and cannot be mapped directly onto the capital–labor elasticity estimates reported in the literature. The distinction matters for Proposition 2.

Each task can be performed by labor or by capital. Let the interval of tasks capital is able to perform be $[0,I]$, where is the automation boundary; tasks in can be performed only by labor. The capability frontier determines which tasks can be automated, and it is treated here as an exogenous state of technology rather than a function of factor prices. Section 4 relaxes the assumption.

To concentrate on the extensive margin, assume that productivity within a task does not vary with the task index:

$$y(i)=\begin{cases} A_K\, k(i), & i\in[0,I] \\ A_L\, l(i), & i\in(I,N] \end{cases} \tag{2}$$

where and are the capital and labor used in task i, and and are the within-task productivities of capital and labor. Equation (2) assumes that automated tasks use capital alone. The simplification is justified

because capital enjoys a strict cost advantage on tasks that can be automated, so labor is not employed there in equilibrium. When both factors can be used, the boundary is determined endogenously by factor prices; Section 4 takes up that case.

3.2 Factor Demand and Prices

The final-good market is perfectly competitive, and the firm chooses task inputs taking as given. Cost minimization gives task demand as

$$y(i)=Y\left(\frac{p(i)}{P}\right)^{-\sigma} \tag{3}$$

where is the price of the final good, that is, the constant-elasticity aggregate of task prices:

$$P=\left[\int_0^N p(i)^{1-\sigma}\mathrm{d}i\right]^{\frac{1}{1-\sigma}} \tag{4}$$

The market for tasks is likewise perfectly competitive. Since each task uses only one factor, its price equals the unit factor cost:

$$p(i)=\begin{cases}R/A_K, & i\in[0,I]\\ w/A_L, & i\in(I,N]\end{cases} \tag{5}$$

where is the rental rate of capital and is the wage rate.

Substituting (5) into factor demand gives aggregate demand for capital and labor:

$$K=\int_0^I k(i)\,\mathrm{d}i=YR^{-\sigma}P^{\sigma}\Lambda_K,\qquad \Lambda_K\equiv\int_0^I \gamma_K(i)^{\sigma-1}\mathrm{d}i \tag{6}$$

$$L=\int_I^N l(i)\,\mathrm{d}i=Yw^{-\sigma}P^{\sigma}\Lambda_L,\qquad \Lambda_L\equiv\int_I^N \gamma_L(i)^{\sigma-1}\mathrm{d}i \tag{7}$$

where and $\gamma_L(i)=A_L$. The terms and describe the effective scale of capital tasks and of labor tasks, and are the central state variables of the model. Under constant productivity they reduce to

$$\Lambda_K=A_K^{\sigma-1}I,\qquad \Lambda_L=A_L^{\sigma-1}(N-I) \tag{8}$$

The price index in (4) can then be written as

$$P^{1-\sigma}=R^{1-\sigma}\Lambda_K+w^{1-\sigma}\Lambda_L \tag{9}$$

Equations (6) and (7) verify that $wL+RK=YP$: factor rewards exhaust total output, as they must under constant returns to scale.

3.3 A Closed-form Solution for the Labor Income Share

The labor income share is labor compensation as a share of total output:

$$S_L\equiv\frac{wL}{PY} \tag{10}$$

Substituting (7) into (10) and using (9) to eliminate gives

$$S_L=\frac{w^{1-\sigma}\Lambda_L}{w^{1-\sigma}\Lambda_L+R^{1-\sigma}\Lambda_K} \tag{11}$$

Taking the price of capital as the numeraire, set $R=1$. Dividing (6) by (7) yields the equilibrium wage:

$$\frac{L}{K}=\frac{w^{-\sigma}\Lambda_L}{\Lambda_K}\quad\Rightarrow\quad w^{\sigma}=\frac{K}{L}\cdot\frac{\Lambda_L}{\Lambda_K} \tag{12}$$

Substituting (12) into (11) and simplifying gives

$$S_L=\frac{1}{1+\left(\frac{K}{L}\right)^{\frac{\sigma-1}{\sigma}}\left(\frac{A_K}{A_L}\right)^{\frac{1}{\sigma}}} \tag{13}$$

Equation (13) is the first of the paper's two central results: the labor income share is determined entirely by the capital–labor ratio and by the ratio of the effective scale of capital tasks to that of labor tasks. Define

$$\kappa\equiv\frac{A_K K}{A_L L},\qquad a\equiv\frac{I}{N-I} \tag{14}$$

where is efficiency-adjusted capital intensity and is the breadth of automation, the number of automated tasks relative to the number of labor tasks in effective terms. Substituting (8) into (13) gives

$$S_L=\frac{1}{1+\kappa^{\frac{\sigma-1}{\sigma}}a^{\frac{1}{\sigma}}} \tag{15}$$

Equation (15) is the central equation of the paper. It writes the labor income share as an explicit function of efficiency-adjusted capital intensity κ, the breadth of automation and the elasticity of substitution σ: the share depends on the product of capital's numerical advantage over labor, captured by κ, and capital's coverage advantage, captured by a, while governs how these advantages translate into shares.

As a check, let $\sigma\to1$. Equation (15) then collapses to $S_L=1/(1+a)=(N-I)/N$, so that the share equals the fraction of tasks not automated. This agrees with the Cobb–Douglas intuition and with the limiting form obtained by the task framework when the elasticity of substitution equals one [7].

3.4 Comparative Statics and the Four Propositions

Taking logarithms of (15) gives

$$\ln S_L=-\ln\left(1+\kappa^{\frac{\sigma-1}{\sigma}}a^{\frac{1}{\sigma}}\right) \tag{16}$$

Write $X\equiv\kappa^{(\sigma-1)/\sigma}a^{1/\sigma}=S_K/S_L$, where is the capital income share. Differentiating (16) yields the two basic elasticities:

$$\frac{\partial\ln S_L}{\partial\ln a}=-\frac{1}{1+X}\cdot\frac{1}{\sigma}\cdot X=-\frac{1-S_L}{\sigma} \tag{17}$$

$$\frac{\partial\ln S_L}{\partial\ln\kappa}=-\frac{1-S_L}{\sigma}\cdot(\sigma-1) \tag{18}$$

The four propositions follow.

Proposition 1 (displacement effect). Given and σ, an increase in the breadth of automation always lowers the labor income share, and

$$\frac{\partial\ln S_L}{\partial\ln a}=-\frac{1-S_L}{\sigma}<0 \tag{19}$$

Its absolute value is decreasing in σ: the stronger the substitutability among tasks, the smaller the marginal erosion of the share caused by automation.

The proof is immediate from (17). The direction does not depend on the size of the substitution

elasticity, nor on the direction of capital deepening: as long as the automation boundary moves outward while is held fixed, the share falls. This is consistent with the directional result on automation in the task framework [7]; what the present paper adds is the explicit form of the elasticity.

The precise meaning of "given" needs stating. It refers to the partial derivative with respect to at fixed and σ. If a single technology shock moves and together, as under the endogenous boundary of Section 4, the total effect is given by (22); when the channel is positive and the channel negative, so the share falls only if the automation-breadth channel dominates, that is, if $\mathrm{d}\ln a > -(\sigma-1)\mathrm{d}\ln\kappa$. Proposition 1 is therefore a statement about a partial effect, not a verdict on the total effect of an arbitrary technology shock.

Equation (19) also delivers a conclusion easily overlooked: the larger is, the smaller the marginal effect of the breadth of automation, because handing a subset of easily substitutable tasks to capital does not much alter the relative price structure of the final good. But also affects the level of the share through $\kappa^{(\sigma-1)/\sigma}$: when $\kappa>1$, a larger means a lower share at given a. The total effect of combines a level effect and an elasticity effect and cannot be inferred from (19) alone.

Proposition 2 (capital intensity effect). Given and σ, the direction of the effect of a rise in efficiency-adjusted capital intensity on the labor income share depends on the elasticity of substitution across tasks:

$$\frac{\partial \ln S_L}{\partial \ln \kappa} = \begin{cases} <0, & \sigma>1 \\ =0, & \sigma=1 \\ >0, & \sigma<1 \end{cases} \tag{20}$$

The proof is immediate from (18). This is where the paper departs most sharply from the popular judgement that artificial intelligence must lower the labor share. When $\sigma<1$, tasks are complements: an improvement in capital efficiency lowers the price of capital tasks and, through complementarity, expands demand for labor tasks by enough to offset the rise in the capital share. The result is not new — it restates the established relationship between capital-augmenting technical change and the labor share [6] — but placing it within the task framework yields a clearer mechanism.

The two components of deserve distinguishing. By (14), contains both within-task technical efficiency and the capital–labor ratio K/L. They act through the same channel here but are not the same thing economically: a rise in is technical progress, whereas a rise in may reflect a high saving rate, a fall in the price of investment goods, or distorted factor prices. The baseline model treats them jointly for simplicity, at the cost of not separating the two sources; Section 4, by endogenizing the boundary, isolates A_K. When reading Proposition 2, is best understood as a composite measure of efficiency-adjusted capital intensity, not as the level of artificial intelligence technology alone.

The policy implication is important. If the elasticity of substitution across tasks in China is below one, a rise in capital intensity on its own works against capital, and what actually depresses the labor share is automation itself. The focus of policy debate should therefore shift from whether to develop artificial intelligence to the speed and scope of automation. Section 5 returns to this point.

Proposition 3 (creation effect). Given and σ, new task creation (a rise in N) lowers the breadth of automation and therefore raises the labor income share, with

$$\frac{\partial \ln S_L}{\partial \ln N} = \frac{1-S_L}{\sigma} \cdot (1+a) > 0 \tag{21}$$

Proof. From it follows that $\partial \ln a / \partial \ln N = -N/(N-I) = -(1+a)$; substituting into (17) gives (21).

Comparing (19) with (21), the two elasticities carry opposite signs, share the same functional form, and (21) is exactly times as large in absolute value. The factor reflects the dilution of the breadth of automation by new tasks: the larger a, the smaller the proportion by which a given number of new tasks can dilute it.

Propositions 1 and 3 form a symmetric pair. If new tasks grow at the same rate as automated tasks, so that $\mathrm{dln}(N-I) = \mathrm{dln} I$, then is unchanged and so is the share. The contest between displacement and creation is thus a contest between two rates of task growth rather than between two directions of technology.

Proposition 4 (a stability condition for the labor income share). Totally differentiating (16) gives

$$\mathrm{dln} S_L = -\frac{1-S_L}{\sigma} [(\sigma-1)\, \mathrm{dln}\kappa + \mathrm{dln} a] \tag{22}$$

The labor income share therefore remains unchanged if and only if

$$(\sigma-1)\, \mathrm{dln}\kappa + \mathrm{dln} a = 0 \tag{23}$$

Substituting $\mathrm{dln} a = \mathrm{dln} I - \mathrm{dln}(N-I)$, this is equivalent to

$$\mathrm{dln}(N-I) = (\sigma-1)\, \mathrm{dln}\kappa + \mathrm{dln} I \tag{24}$$

Proposition 4 is the central result of the paper. It converts the question of whether the share can be stabilized into a condition that can be checked term by term: the growth rate of labor tasks must equal the growth rate of automated tasks plus times the rate of efficiency-adjusted capital deepening. Three special cases clarify what it says.

First, when $\sigma=1$, equation (24) collapses to $\mathrm{dln}(N-I) = \mathrm{dln} I$: new tasks need only grow at the same rate as automation for the share to remain constant, consistent with the Cobb–Douglas case in which the share equals the fraction of tasks.

Second, when and capital deepens continuously, labor tasks must grow faster than automated tasks to offset the negative effect of capital deepening. This explains why maintaining the labor share in an economy that accumulates capital rapidly requires stronger task creation.

Third, when $\sigma<1$, capital deepening itself raises the labor share, so the share can remain stable even if automation runs ahead of task creation. This offers a possible route to interpreting the Chinese experience.

Proposition 4 is a condition of the accounting-identity kind. Its value lies not in supplying particular parameter values but in decomposing a vague question — whether technology is favourable to labor — into a comparison among three quantities that can be observed and discussed separately. This is the paper's methodological contribution.

4. Extensions: The Endogenous Automation Boundary and Scenario Analysis

Section 3 treats the automation boundary as an exogenous state of technology. The treatment makes the

closed form tractable but neglects an important mechanism: which tasks are automated is itself a function of factor prices. This section relaxes the assumption and then uses the resulting model for a set of scenario calculations.

4.1 An Endogenous Automation Boundary

Suppose that productivity declines with task complexity. The larger the task index i, the more complex the task and the lower the relative efficiency of artificial intelligence on it:

$$\gamma_K(i)=A_K e^{-\theta i}, \qquad \gamma_L(i)=A_L, \qquad \theta>0 \tag{25}$$

The parameter measures how fast the capability of artificial intelligence decays with task complexity; a smaller means it can handle more complex tasks.

This alters the meaning of A_K, which is no longer a constant productivity applying to every automated task but the level of efficiency at the origin of the task space, declining with the task index. Correspondingly, in (14) becomes capital intensity adjusted by the average efficiency over the interval of capital tasks:

$$\kappa \equiv \frac{K}{L}\left(\frac{\Lambda_K}{A_L^{\sigma-1} I}\right)^{\frac{1}{\sigma-1}}$$

When is identically A_K, the expression reduces to $\kappa=A_K K/(A_L L)$, consistent with (14). Under (25), is the average of over $[0,I]$, and the direction in which it moves with depends on σ. This section therefore uses only as a composite state variable, and the scenario analysis below retains constant productivity to remain comparable with Section 3.

Under perfect competition, the price of task if automated is $R/(A_K e^{-\theta i})=Re^{\theta i}/A_K$, and its price if performed by labor is w/A_L. The firm chooses the cheaper method, so the automation boundary is determined by

$$\frac{Re^{\theta I}}{A_K}=\frac{w}{A_L} \quad \Rightarrow \quad I=\frac{1}{\theta}\ln\frac{A_K w}{A_L R} \tag{26}$$

Equation (26) yields two comparative statics of interest:

$$\frac{\partial I}{\partial \ln A_K}=\frac{1}{\theta}>0, \qquad \frac{\partial I}{\partial \ln w}=\frac{1}{\theta}>0 \tag{27}$$

The first says that an improvement in the capability of artificial intelligence extends the automation boundary, and that the smaller is, the faster the extension. The second says that a rise in the wage also extends the boundary, which is the induced-innovation hypothesis restated in the language of tasks [8]: when labor becomes expensive, firms hand more tasks to capital.

It should be stressed that (26) is a partial-equilibrium result taking the wage as given. In general equilibrium the wage is determined by (12); since falls as rises, the wage falls relative to the rental rate as automation proceeds. The feedback is negative, so the boundary described by (26) is self-correcting: what drives it outward over time is a rise in A_K, not the endogenous adjustment of wages. Absent progress in the capability of artificial intelligence, rising labor costs alone will not generate unbounded automation.

Once the boundary is endogenous, a previously suppressed question surfaces: a rise in moves two variables at once. By (14) it enters the numerator of directly; by (26) it extends and thereby raises a. The net effect therefore cannot be read off Propositions 1 or 2 alone but must be determined from (22), whose sign depends on $(\sigma\text{-}1)\mathrm{d}\ln\kappa+\mathrm{d}\ln a$. When the two terms share a sign and the share necessarily falls; when they oppose each other, and the net effect depends on whether the breadth of automation expands faster than the compensation from the rise in κ. The propositions of Section 3 are thus partial effects, and for the total effect requires both channels to be examined together.

4.2 Parameter Values and Scenarios

To illustrate the quantitative content of (15), this section conducts a sensitivity analysis. It is not a calibration but a scenario exercise: parameters are chosen so that the model reproduces the order of magnitude of the Chinese labor income share, and the marginal effects of the several variables are then read off.

The elasticity of substitution across tasks, σ, is set at 0.6, 0.8, 1.0, 1.2 and 1.5. The range covers both task complementarity ($\sigma<1$) and task substitutability ($\sigma>1$) without prejudging the estimates reported in the literature.

Efficiency-adjusted capital intensity, κ, is set at 3, so that the model delivers when and σ=0.8, within the range commonly reported for China. Which measure 0.44 corresponds to needs stating, or the anchor will be insecure: estimates of the Chinese labor income share are highly sensitive to the convention adopted. On the income approach, employee compensation fell to about 40 percent of GDP around 2007 and has recovered to around 45 percent; the flow-of-funds accounts give a markedly higher level, and separating the employee from the self-employed economy changes it again [2,5]. The value 0.44 to 0.45 is adopted here as a scenario anchor, roughly the income-approach level of 2007 to 2011. This does not affect the conclusions: the level of determines only the level of the share, not its direction of movement, so under a higher convention would simply be scaled down and the entries of Table 1 would shift as a whole while the elasticities and sign results stayed unchanged.

4.3 Simulation Results

Table 1 reports the labor income share for alternative combinations of and a.

Table 1. Sensitivity of the Labor Income Share (κ=3)

Breadth of automation a	σ=0.6	σ=0.8	σ=1.0	σ=1.2	σ=1.5
0.8	0.751	0.635	0.556	0.501	0.446
1.0	0.675	0.568	0.500	0.454	0.409
1.2	0.606	0.512	0.455	0.417	0.380
1.5	0.514	0.442	0.400	0.373	0.346
1.75	0.450	0.395	0.364	0.343	0.323

2.0	0.396	0.356	0.333	0.318	0.304
2.5	0.311	0.295	0.286	0.280	0.273

Note: Values are computed from Equation (15) with κ=3. The breadth of automation is defined as $a=I/(N-I)$, the ratio of automated tasks to labor tasks.

Table 1 conveys three messages.

First, the labor income share is most sensitive to the breadth of automation. At σ=0.8, a rise in from 1.0 to 1.75 lowers the share from 0.568 to 0.395, a decline of 17.3 percentage points, whereas raising by 75 percent at a=1.75, from 3 to 5.25, restores it to 0.429. The role of the breadth of automation in the long Chinese decline may therefore have been understated.

Second, determines both the level of the share and the sensitivity of the responses: a larger means a lower share at given but a smaller marginal effect of a. At σ=0.6, a rise in from 1.5 to 1.75 lowers the share by 6.4 percentage points; at the same change lowers it by only 2.3 percentage points. An economy in which tasks substitute readily is therefore more tolerant of automation, but once automation reaches a high level the share itself is already low.

Third, when σ<1, capital intensity and automation push the share in opposite directions. To compare the two channels, let rise from 3 to 4. With and held at 1.5, the share rises from 0.442 to 0.460; but if the rise in is accompanied by a rise in from 1.5 to 1.75, the share falls to 0.413. Whether the dividend from higher capital intensity is converted into a better labor share depends on whether the advance of automation is held in check.

Figure 1 plots Table 1 as curves and makes the first two propositions easier to see. Every curve declines monotonically as the breadth of automation rises, steepest at low and flattening thereafter, which is Proposition 1. The position of a curve is governed by σ: the larger σ, the lower the share at given a. The dashed lines show the position after rises from 3 to 4: the dashed curve for lies above its solid counterpart and that for below its own, the two moving in opposite directions, which is the content of Proposition 2.

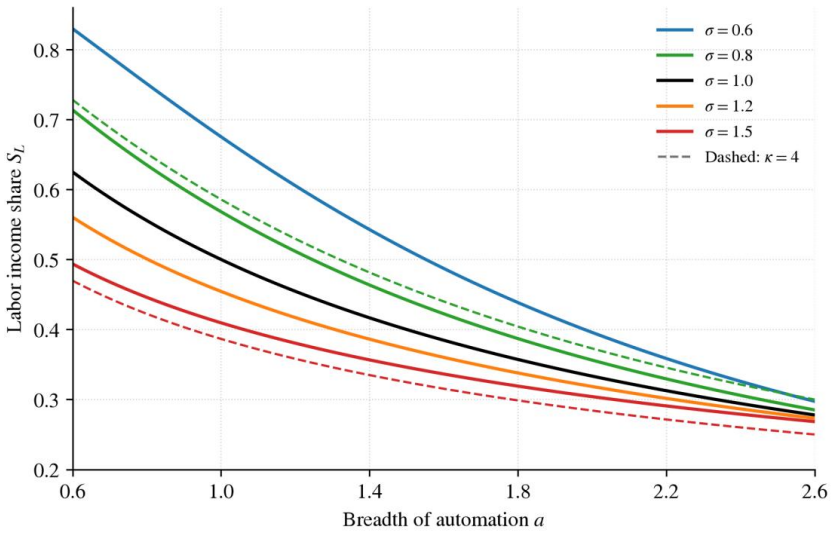


Figure 1. Labor Income Share as a Function of the Breadth of Automation (κ=3 for solid lines, for dashed lines)

As a scenario projection, under the stated parameters suppose that China currently has σ=0.8, and S_L=0.45. Solving (15) backwards gives a≈1.46, corresponding to I/N≈0.59, so that about 59 percent of tasks have been automated. If generative artificial intelligence raises the breadth of automation by about 21.5 percent, to and I/N≈0.64, the share falls to about 0.391, a decline of 5.9 percentage points. From the same initial share and with the same advance in automation, a value of would lower the share only to about 0.410, a decline of 4.0 percentage points.

These magnitudes are conditional: they hold only when σ=0.8, and an initial share of 0.45 obtain at once. A higher initial share under a different convention, or a near one, would change them appreciably, while would merely shift the level. Two results are robust: the share is highly sensitive to the breadth of automation, and that sensitivity declines as rises. How hard generative artificial intelligence hits the distribution therefore depends largely on which interval the elasticity of substitution in the Chinese economy falls into — a question on which empirical research has yet to return a robust answer.

4.4 Summary

The partial-effect results of Section 3 survive the relaxation of constant productivity, provided they continue to be read as partial effects. Endogenizing the boundary adds two drivers, an improvement in the capability of artificial intelligence and a rise in labor costs; the former moves and together, so its net effect must be judged from (22). The scenario analysis shows that the breadth of automation is the most powerful variable in accounting for movements in the share, considerably more so than capital intensity.

5. The Chinese Experience and Policy Implications

The Chinese labor income share traces a sequence of decline, trough and stabilization that no single explanation in the existing literature accounts for in full. This section argues that the sequence is organized by the breadth of automation, and that the forces that moved it at different times can be located within the model. It then turns to the implications for policy.

5.1 Capital Deepening and Expanding Automation, 1995 to 2007

The Chinese labor income share fell markedly after the mid-1990s; estimates of the magnitude differ with the measurement convention but generally exceed 10 percentage points [2,3]. Within the present framework, two things happened at once.

The first was a rapid rise in efficiency-adjusted capital intensity. Industrialization in heavy and chemical industries, infrastructure investment and the recapitalization of state-owned enterprises caused the capital stock to accumulate quickly relative to effective labor, while the transfer of rural labor depressed wages and raised further. By Proposition 2, this depresses the labor share if and raises it if σ<1; since the share was falling, it follows either that or that the effect of was overwhelmed by the rise in the breadth of automation.

The second was an expansion of the breadth of automation. Chinese manufacturing shifted from labor-intensive to capital-intensive techniques, as numerically controlled machine tools and automated production lines spread on a large scale; China became the world's largest market for industrial robots in 2013, and its share of global installations has risen since. These changes extended directly and thereby raised a, which by Proposition 1 depresses the labor share, other things equal.

The relative importance of the two can be judged from Table 1. At σ=0.8, a rise in from 1.0 to 1.75 lowers the share by 17 percentage points, whereas a rise in from 3 to 4 raises it. Within the parameter range the model admits, the Chinese decline therefore came mainly from the expansion of the breadth of automation rather than from capital deepening. This differs from the capital-deepening explanation and prepares the account of the turning point: if the decline came mainly from a, the share should stabilize once stops rising. The inference depends on σ<1; if the elasticity of substitution across tasks in China is in fact above one, capital deepening and automation press the share down in the same direction, and theory alone cannot apportion the decline between them.

5.2 New Task Creation and the Stabilization of the Share after 2007

After 2007 the labor income share ended a decline that had lasted more than a decade, stabilized at a low level and began a slow recovery around 2011 [4]. The argument of this paper is that the turning point came from accelerated new task creation together with restraint of the automation boundary, so that stopped rising. Three channels are at work, and because they correspond to different variables they need to be distinguished.

The first is the expansion of the service sector, corresponding to a rise in combined with a slowing of the expansion of I. The tertiary sector's share of value added first exceeded that of the secondary sector in 2013, has risen since, and reached about 54.6 percent in 2023. Within the framework, services lower in two ways. New service activities extend the task space, so rises; and by (25), service tasks depend heavily on interpersonal interaction and contextual judgement, so the relative efficiency of artificial intelligence declines faster with complexity — that is, is larger — and the boundary in (26) expands more slowly. A rise in with a slowing of lowers $a=I/(N-I)$, which by Proposition 3 raises the labor share.

The second is the rise of the platform economy and of new forms of employment. This channel needs care: the tasks involved in food delivery, ride-hailing and live-stream commerce are not additions to the task space in concept, and what the platform economy changes is mainly the organization of those tasks and the cost of transacting over them. Its counterpart in the model should therefore be written as an inward movement of rather than an expansion of N: by improving matching efficiency and reducing transaction costs, platforms raise the effective productivity of labor, A_L, on existing tasks, and by (26) falls as rises, which lowers and raises the labor share. This reading fits the roughly 84 million workers now in new forms of employment — labor regaining a cost advantage on existing tasks, not an expansion of the task space — and it has content: counted as an expansion of N, the platform economy would be indistinguishable from the other creation channels and could not be shown to be especially effective on low-skilled tasks.

The third is the twofold effect of rising labor costs. By (27), a rise in wages extends the automation boundary, working against the labor share, but it also expands demand for services and accelerates the creation of new tasks. The stabilization of the share after 2007 indicates that the second effect has been at least as strong as the first. The judgement connects with the analysis of the Lewis turning point [28] but emphasizes a different channel: its distributional consequence lies not only in higher wages but in a change in the direction of technical change.

5.3 Why China and the United States diverged

Why, in the face of a single technological wave, did the Chinese labor income share stabilize after 2007 while the decline in the United States has not visibly reversed? The framework offers a unified answer that does not require the two economies to face different technologies.

By Proposition 4, the trajectory of the share depends on the relative magnitude of and $(\sigma\text{-}1)\mathrm{d}\ln\kappa+\mathrm{d}\ln I$. The difference can be located at three points.

The first is the source of task creation. In China it has been driven largely by the expansion of services and by the platform economy, and such tasks have low skill thresholds and high labor intensity, so they absorb quickly the labor displaced by automation. In the United States task creation is concentrated in high-skill services, where expansion is constrained by the supply of qualified labor and the pull on is correspondingly weaker. This explains why has held steady in China while rising in the United States at a comparable rate of automation.

The second is the elasticity of substitution. If is lower in China than in the United States, then by Proposition 2 capital deepening in China raises the labor share and thereby offsets part of the negative effect of automation automatically, whereas in the United States a higher means that capital deepening and automation press the share down together.

The third is the institutional environment. The coverage of minimum wages, collective bargaining and social insurance affects the strength with which rising wages are transmitted into automation. By (27), a rise in wages extends the automation boundary, but the strength of that transmission depends on the room for adjustment available to firms.

These three points are possible explanations implied by the framework, not tested conclusions. Their purpose is to show that the model need not assign different technology shocks to the two economies: differences in the rate of task creation, in the elasticity of substitution and in the institutional environment suffice to generate different distributional trajectories. That is itself an advantage of the task framework over technological-determinist explanations.

5.4 The Generative Artificial Intelligence Turning Point

Since late 2022, generative artificial intelligence built on large pre-trained models has spread rapidly. Its decisive difference from earlier automation technologies is that the boundary of automation has moved from routine manual tasks to routine cognitive ones: drafting text, writing code, analyzing data and answering customers, once regarded as hard to automate because they require language comprehension and contextual judgement, now fall within the capability of the technology.

Within the present framework, the change acts on two parameters of (26) at once. First, rises: artificial intelligence becomes more efficient per task. Second, falls: its capability decays more slowly with task complexity, so it can handle more complex tasks. Together they make the automation boundary expand faster.

The labor share need not fall, because a rise in also raises κ. By (22), the net change depends on $(\sigma\text{-}1)\mathrm{d}\ln\kappa+\mathrm{d}\ln a$: under task substitutability the two channels share a sign and the share necessarily falls, whereas under complementarity they oppose one another and the share falls only if $\mathrm{d}\ln a>-(\sigma\text{-}1)\mathrm{d}\ln\kappa$.

What is distinctive about generative artificial intelligence is that it can be replicated across many cognitive tasks at almost zero marginal cost, so is very likely to exceed the compensating term from capital deepening. The conditional judgement of this paper is therefore that it will lower the labor income share whenever the automation-breadth channel dominates — unconditionally for $\sigma>1$, by comparison of expansion rates otherwise.

More troubling, the new tasks created by generative artificial intelligence may have higher skill thresholds than those it displaces. Industrial automation displaced assembly-line workers and created posts in equipment maintenance and programming; generative artificial intelligence displaces junior white-collar workers and creates posts in model training, prompt engineering and model governance. Whether the latter will suffice in number to offset the former is unsettled: if $\mathrm{d}\ln(N\text{-}I)<(\sigma\text{-}1)\mathrm{d}\ln\kappa+\mathrm{d}\ln I$, then by Proposition 4 the share will re-enter a declining path.

5.5 Policy Implications

The analysis points to a conclusion that runs against intuition: what matters in responding to the distributional shock of artificial intelligence is not restraining automation but sustaining the rate of new task creation. Proposition 1 establishes that automation erodes the share, other things equal, so protecting it by delaying technology costs productivity; Propositions 3 and 4 establish that, provided new tasks are created fast enough, the share can be held at any desired level. Four proposals follow.

First, lower the cost of task creation through new infrastructure. New tasks do not appear of their own accord; their creation depends on the availability of data, computing power and application settings. As a general-purpose technology with substantial spillovers, artificial intelligence has the character of new infrastructure and calls for public investment [20].

Second, raise the comparative advantage of labor on new tasks through vocational training. The force of Proposition 3 depends on labor being able to enter the tasks that are newly created. If the skill threshold of new tasks is too high for labor to cross, an expansion of will not translate into an expansion of $N\text{-}I$. The objective should therefore not be a general upgrading of skills but a targeted cut in the cost of entering new tasks, matched to the skills they require.

Third, compensate the costs of transition through social insurance and redistribution. Proposition 4 is an aggregate condition, and stability in the aggregate does not mean that no one loses: automation raises total output while exposing workers on particular tasks to concentrated shocks. Without compensation, the political sustainability of the distribution is at risk even when the share is stable.

Fourth, monitor the breadth of automation statistically. The central variable of this paper, a, is not directly observable in the existing statistical system; indicators by industry and occupation could be built from recruitment platform data, occupational task databases and firm surveys. Without such an indicator, policymakers cannot tell whether the economy is approaching the threshold described by Proposition 4.

6. Conclusion

This paper has built a task-based model with a continuum of tasks to study how artificial intelligence affects the labor income share. Four results stand out.

First, the labor income share can be written as an explicit function of the breadth of automation, efficiency-adjusted capital intensity and the elasticity of substitution across tasks. The closed form converts a question that admits no general answer — whether artificial intelligence lowers the labor share — into a quantitative condition whose terms can be compared one by one.

Second, given capital intensity, a rise in the breadth of automation always lowers the labor income share, with an elasticity whose direction does not depend on the substitution elasticity, whereas the effect of capital intensity does depend on it, being negative when and positive when $\sigma<1$. The judgement that artificial intelligence must lower the labor share therefore holds only within a particular parameter range; when the net effect depends on a comparison between the two channels.

Third, new task creation raises the labor income share by lowering the breadth of automation, with an elasticity of the opposite sign, the same functional form, and exactly times the magnitude of the displacement effect. The contest between displacement and creation is at bottom a contest between two rates of task growth.

Fourth, a necessary and sufficient condition for a constant labor income share is that the growth rate of labor tasks equal that of automated tasks plus times the rate of efficiency-adjusted capital deepening. Applied to China, it suggests that the stabilization after 2007 came from the extension of the task space through services, the inward movement of the automation boundary through the platform economy, and the twofold effect of rising labor costs, which together held back the rise in the breadth of automation; and that generative artificial intelligence, by pushing automation into routine cognitive tasks, may disturb that balance once again.

The paper has several limitations. First, the model is static, so it cannot address the effect of artificial intelligence on the long-run growth path. Second, perfect competition and full employment confine the analysis to shares rather than employment and leave out an important mechanism: imperfect competition in product and labor markets itself alters the distributional consequences of artificial intelligence. Firm-level evidence indicates that the erosion of monopsony power is an important channel through which artificial intelligence improves the distribution between capital and labor [27], which the competitive setup here cannot capture — one source of the tension between this framework and firm-level evidence. Third, labor is homogeneous, so skill heterogeneity and the skill premium are

not discussed. Fourth, the quantitative conclusions depend critically on the elasticity of substitution and on efficiency-adjusted capital intensity, neither of which empirical work yet estimates robustly, so the scenario analysis delivers only conditional conclusions. Fifth, the paper does not examine these shocks in an open economy, where the reorganization of global value chains may amplify or offset the mechanisms described.

These limitations also indicate directions for further work: to introduce capital accumulation and skill heterogeneity into a dynamic general-equilibrium framework, to estimate the elasticity of substitution across tasks and the breadth of automation from micro data, and to examine the distributional effects of artificial intelligence operating through international trade and global value chains.

References

[1] Karabarbounis L, Neiman B. The global decline of the labor share. Quarterly Journal of Economics. 2014; 129(1):61-103.

[2] Bai Chongen, Qian Zhenjie. Who is crowding out household income: An analysis of the national income distribution pattern in China. Social Sciences in China. 2009; (5):99-115.

[3] Luo Changyuan, Zhang Jun. An economic explanation for the decline in the labor income share: Evidence from Chinese provincial panel data. Management World. 2009; (5):26-35.

[4] Liu Yalin, Mao Rui, Yao Yang. Structural transformation, the financial crisis and changes in the labor income share in China. China Economic Quarterly. 2018; 17(2):609-632.

[5] Zhang Juwei, Zhao Wen. The labor compensation share in China: Measurement and analysis of the employee and self-employed economies. Social Sciences in China. 2015; (12):90-112.

[6] Acemoglu D. Labor- and capital-augmenting technical change. Journal of the European Economic Association. 2003; 1(1):1-37.

[7] Acemoglu D, Restrepo P. The race between man and machine: Implications of technology for growth, factor shares, and employment. American Economic Review. 2018; 108(6):1488-1542.

[8] Hicks J. The Theory of Wages. London: Macmillan; 1932.

[9] Harrod R. Towards a Dynamic Economics. London: Macmillan; 1948.

[10] Solow R. Technical change and the aggregate production function. Review of Economics and Statistics. 1957; 39(3):312-320.

[11] Acemoglu D. Directed technical change. Review of Economic Studies. 2002; 69(4):781-809.

[12] Autor D, Levy F, Murnane R. The skill content of recent technological change: An empirical exploration. Quarterly Journal of Economics. 2003; 118(4):1279-1333.

[13] Acemoglu D, Autor D. Skills, tasks and technologies: Implications for employment and earnings. Handbook of Labor Economics, Volume 4B. Amsterdam: Elsevier; 2011. p. 1043-1171.

[14] Acemoglu D, Restrepo P. Automation and new tasks: How technology displaces and reinstates labor. Journal of Economic Perspectives. 2019; 33(2):3-30.

[15] Acemoglu D, Restrepo P. Robots and jobs: Evidence from US labor markets. Journal of Political Economy. 2020; 128(6):2188-2244.

[16] Graetz G, Michaels G. Robots at work. Review of Economics and Statistics. 2018; 100(5):753-768.

[17] Korinek A, Stiglitz J. Artificial intelligence, globalization, and strategies for economic development. Cambridge, MA: National Bureau of Economic Research; 2021. NBER Working Paper No. 28453.

[18] Chen Dong, Qin Ziyang. Artificial intelligence and inclusive growth: Evidence from global industrial robot use. Economic Research Journal. 2022; (4):85-102.

[19] Wang Linhui, Yuan Li. Biased technical change, industrial structure change and the factor income distribution pattern in China. Economic Research Journal. 2018; (11):60-78.

[20] Guo Kaiming. Artificial intelligence development, industrial structure upgrading and changes in the labor income share. Management World. 2019; (7):60-77.

[21] Chao Xiaojing, Zhou Wenhui. The effect of artificial intelligence on the labor income share: A theoretical explanation and empirical test from the perspective of skill bias. Research on Economics and Management. 2021; 42(2):82-94.

[22] Huang Haoquan, Dai Tianshi, Shen Jun. Artificial intelligence development, the learning-by-doing effect and the skill premium: An analysis based on a model of endogenous technical change. China Industrial Economics. 2024; (2):99-117.

[23] Acemoglu D. The simple macroeconomics of AI. Economic Policy. 2025; 40(121):13-58.

[24] Huang Zhuo, Tao Yunqing, Liu Zhaoda, Ye Yongwei. Intelligent manufacturing, human capital upgrading and the labor income share of firms. China Economic Quarterly. 2024; 24(5):1412-1427.

[25] Chen Lin, Gao Yuepeng, Yu Linhui. How does artificial intelligence change the demand of firms for labor? Evidence from recruitment platform big data. Management World. 2024; (6):74-92.

[26] Liu Dongsheng, Wang Yongzhong. Artificial intelligence, task restructuring and the distribution of technology dividends. Journal of Finance and Economics. 2026; 52(8):49-63.

[27] Su Zhi, Li Ying, Cheng Zhiyuan. How does artificial intelligence reshape the factor income distribution pattern? Micro evidence based on the labor market power of firms. Economic Research Journal. 2025; (9):218-238.

[28] Cai Fang. Demographic transition, the demographic dividend and the Lewis turning point. Economic Research Journal. 2010; (4):4-13.