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Productivity Without Prosperity? Who Captures the Economic Gains from Workplace Artificial Intelligence?

Sarfaraz Abu Abdullah

rajon3430@gmail.com

University of Rajshahi https://orcid.org/0009-0000-3826-1626

Research Article

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Research article

Productivity Without Prosperity? Who Captures the Economic Gains from Workplace Artificial Intelligence?

Abstract

Experiments show that generative AI raises productivity on specific tasks by 14 to 40 percent, but who benefits when it spreads through the economy is far less clear. This study builds a capture accounting from task to economy. It links published field and survey evidence on productivity gains, adoption and wage pass-through to an exact decomposition of productivity gains in the U.S. nonfarm business sector, using the Bureau of Labor Statistics (BLS) release of 5 November 2026 and the Census Bureau's Business Trends and Outlook Survey. Between the first quarter of 2024 and the third quarter of 2026, output per hour rose by 6.35 log points; 3.28 points (51.7 percent; rounding interval 50.3 to 53.1) reached workers as higher compensation relative to output prices, and 3.07 points went to nonlabor income as the labor share fell to 53.0 percent, the lowest since 1947. Labor's capture fell from 84 percent in 2024 to 70 percent in 2025 and turned negative (-16 percent) in the four quarters to 2026 Q3, while nonfinancial corporate unit profits rose 16.1 percent. At the worker level, Danish administrative data show only 3 to 7 percent of productivity gains reaching earnings. A consistency bound combining these pass-through rates with plausible shares of AI in productivity growth implies that AI explains a minority of the rise in nonlabor capture (median 23 percent; 5th to 95th percentile 8 to 38 percent) and cannot be the whole story. The evidence is descriptive and aggregate, and the AI shares are bounds, not estimates.

Purpose - This study asks who captures the economic gains from workplace AI, and how much of the recent shift in the distribution of productivity gains could plausibly be attributed to it.

Design/methodology/approach - The paper combines published task-level, worker-level and firm-level evidence with an exact capture decomposition of BLS quarterly data, rounding-error Monte Carlo intervals, and a consistency analysis that bounds the AI contribution using pass-through rates and adoption arithmetic.

Findings - Roughly half of the recent productivity gain went to workers and half to nonlabor income, with workers' share falling over time and turning negative in the latest quarters. AI use is concentrated in large firms and in information and finance. Pass-through of AI-specific gains to workers is small, but AI can account for only a minority of the shift.

Research limitations/implications - Aggregate indexes are rounded and revised, AI shares of productivity growth are not observed, and field studies are not representative of the economy. The analysis cannot identify causal effects.

Practical implications - Bargaining institutions, training and transparency over how time savings are used are likely to determine capture, and policy should track labor's share of gains alongside productivity.

Social implications - Productivity growth need not translate into prosperity for workers, and young entrants in exposed occupations face distinct employment risk.

Originality/value - The paper provides a transparent accounting that connects micro and macro evidence on AI's distributional effects and quantifies what current data can and cannot say.

Keywords Artificial intelligence, Productivity, Labor share, Wage pass-through, Income distribution, Technology adoption, United States

Paper type Research article

1. Introduction

Every general-purpose technology prompts the same two questions. How much will it raise output, and who will keep the gain? For generative AI, the first question has attracted most of the attention. Randomised and staggered field studies find that AI assistance raises output per worker on specific tasks by double-digit percentages (Noy and Zhang, 2023; Brynjolfsson et al., 2025). Forecasters have translated such findings into large macroeconomic claims. Acemoglu (2025) shows that these translations depend on the share of tasks affected and the average cost saving, and arrives at a far more modest bound of no more than 0.66 percent additional total factor productivity over ten years. The second question, who keeps the gain, has received less quantitative scrutiny. That is the gap this paper addresses.

The question is pressing because aggregate data in the United States have started to send mixed signals. The BLS reported on 5 November 2026 that nonfarm business productivity rose 3.6 percent at an annual rate in the third quarter and 2.1 percent over four quarters, while real hourly compensation rose 1.0 percent over four quarters and the labor share of output fell to 53.0 percent, the lowest level since the series began in 1947 (Bureau of Labor Statistics, 2026). A fall in labor's share while productivity rises is what the phrase "productivity without prosperity" describes. It is tempting to attribute the pattern to AI, but the measured productivity gains might reflect many forces, and the decline in the labor share began long before generative AI appeared (Karabarbounis and Neiman, 2014; Kehrig and Vincent, 2021).

This paper therefore treats the distribution of gains as a problem of accounting before it is a problem of attribution. It makes four contributions. First, it assembles in one place the evidence at each level at which AI gains can be observed: the task, the worker, the firm and the economy. Second, it applies an exact identity to BLS quarterly data to split productivity gains between labor and nonlabor income, with intervals that reflect the rounding of published indexes. Third, it shows that labor's capture of recent productivity gains has fallen and turned negative in the latest quarters. Fourth, it derives a consistency bound that combines the worker-level pass-through measured in Denmark (Humlum and Vestergaard, 2025) with plausible shares of AI in productivity growth, which shows that AI could account for a minority, but not most, of the rise in nonlabor capture.

The analysis is descriptive. The data are aggregates, the AI contribution is bounded and not estimated, and the field studies on which the micro evidence rests are not representative of the economy as a whole. The aim is to indicate what recent evidence implies about the distribution of gains, and what it cannot imply.

Section 2 reviews the literature, Section 3 sets out the framework and hypotheses, Sections 4 and 5 present data and methods, Sections 6 to 8 report results, Section 9 addresses robustness and limits, and Section 10 discusses implications and concludes.

1.1. Research Objectives and Questions

1) Assemble the evidence on AI-related productivity gains and their pass-through at task, worker, firm and aggregate levels.
2) Decompose recent U.S. productivity gains into labor and nonlabor capture, with uncertainty.
3) Describe the concentration of AI use across firm sizes and sectors.
4) Bound the share of the recent shift in capture that AI could explain.
5) Draw implications for bargaining, training, measurement and policy.

Research Questions

RQ1: How large are AI productivity gains at each level, and how much reaches workers?

RQ2: How have U.S. productivity gains been shared between labor and nonlabor income since 2024?

RQ3: Where is AI use concentrated?

RQ4: How much of the shift in capture could AI plausibly explain?

RQ5: Who bears the risk?

2. Literature and Background

2.1. Technology and the distribution of income

Economic theory offers no guarantee that technological gains are shared. In the task-based framework developed by Acemoglu and Restrepo (2019), technology displaces workers from tasks and reinstates them in new ones, and the balance determines the labor share and wages. Acemoglu and Restrepo (2022) attribute a large part of the rise of U.S. wage inequality to automation of tasks previously performed by workers, and Autor (2015) explains why automation has not so far reduced aggregate employment, because tasks are complements as well as substitutes. Whether gains accrue to workers also depends on market structure. Autor et al. (2020) argue that the fall in the labor share is driven by the reallocation of output to "superstar" firms with high markups and low labor shares, and Kehrig and Vincent (2021) show that the decline is concentrated in establishments with already low shares. Stansbury and Summers (2020) connect the decline of worker bargaining power to the weakening link between productivity and pay. Elsby et al. (2013) trace much of the post-2000 decline in the U.S. labor share to offshoring and automation of routine tasks. Differences in pay between firms have also grown, with Barth et al. (2016) and Song et al. (2019) showing that rising inequality is largely between firms. The relevance for AI is that the same technology can be adopted by different firms on very different terms: a firm with market power can keep most of the gain, a firm facing competition may pass it to customers, and a firm with strong worker representation may share it with employees. Which of these dominates is an empirical matter, and the answer may differ by sector.

The old question of the productivity paradox is also relevant. Solow (1987) observed that computers were visible everywhere except in the productivity statistics, and Brynjolfsson et al. (2021) explain such lags with a productivity J-curve in which complementary investments precede measured gains. For AI, this means that measured productivity may understate or overstate the contribution of the technology at any time, and that gains may appear later and unevenly.

2.2. Evidence on generative AI at work

Early field evidence is striking. Brynjolfsson et al. (2025) studied the staggered rollout of an AI conversational assistant among 5,179 customer-support agents and found that issues resolved per hour rose by 14 percent on average and by 34 percent for novice and low-skilled agents, with minimal effect for the most experienced. Noy and Zhang (2023) randomly assigned 453 professionals to use ChatGPT for occupation-specific writing tasks and found that completion time fell by 40 percent and rated quality rose by 18 percent, with larger benefits for the weaker initial performers. Dell'Acqua et al. (2023) assigned 758 consultants to tasks with and without GPT-4 and found large gains on tasks inside the capability frontier but worse performance on a task outside it. These studies suggest that AI compresses skill differences at the task level, though in the support-agent study the most skilled agents registered small declines in some quality measures.

The macroeconomic implications are debated. Eloundou et al. (2024) estimated that around 80 percent of the U.S. workforce could have at least 10 percent of their tasks affected by large language models. Acemoglu (2025) combines exposure estimates with task-level savings to bound the TFP gain at no more than 0.66 percent over ten years, and below 0.53 percent when hard-to-learn tasks are allowed for, and he predicts that AI will widen the gap between capital and labor income. Bick et al. (2024)

documented that generative AI was adopted faster than the personal computer or the internet, with nearly 40 percent of U.S. adults aged 18 to 64 reporting use by late 2024.

2.3. From task gains to earnings

The step from a task gain to an earnings gain has several links. The worker must adopt the tool, time saved must be turned into output or into leisure, the employer must pay for the added output, and the market must not compete the gain away. Humlum and Vestergaard (2025) combined two adoption surveys of 25,000 workers in 11 exposed occupations with matched employer-employee records in Denmark. They find that chatbots are widely used and that most employers encourage them, but that users report time savings of only 2.8 percent of work hours, that effects on earnings and recorded hours are ruled out above 1 percent, and that only 3 to 7 percent of productivity gains are passed through to earnings, more at firms that encourage use. Firm-led investments in training and encouragement raised adoption from 47 to 83 percent. These results caution against extrapolating directly from experiments to the economy. Denmark has high union density and extensive collective bargaining, so pass-through in other labor markets may be lower, not higher, than the Danish estimate, although the short window of observation may understate eventual wage adjustment.

For entrants, adjustment may occur through hiring and not pay. Brynjolfsson et al. (2026), using ADP payroll data through June 2026, find no evidence of economy-wide displacement but report that employment of workers aged 22 to 25 in AI-exposed occupations is 19 percent below where it would be if it had kept pace with less-exposed peers, with adjustment occurring mainly through employment rather than compensation and in occupations where AI automates rather than augments work. The authors present these as early descriptive indicators, not causal estimates.

2.4. Gap

Studies of AI productivity effects focus on gains, and studies of distribution focus on past technologies. Evidence that links the two, showing who captures current gains and how much of the observed shift could be due to AI, is limited. This paper contributes an accounting that does so.

3. Framework and Hypotheses

Figure 1 summarises the framework. A task-level gain is converted into an aggregate productivity gain by adoption and by the share of work affected, the logic captured in Hulten's (1978) theorem and used by Acemoglu (2025). The aggregate gain is then split among workers, owners of capital and consumers. With output price P, hourly compensation w and output per hour π, the labor share is $s = w/(P\pi)$, which implies that the log gain in productivity equals the log gain in the product wage w/P plus the log fall in the labor share. The first term is labor's capture and the second is the nonlabor capture. The identity is exact and does not depend on how productivity growth arises.

The framework distinguishes the average capture of all productivity growth, a macro quantity, from the pass-through of gains from a specific source such as AI, a micro quantity. The two need not coincide. If AI gains pass through at 3 to 7 percent while other gains pass through at higher rates, the aggregate capture is a weighted average, and the share of AI in productivity growth determines how much the aggregate is dragged down. The consistency analysis in Section 5 uses this relation.

> H1: Task-level AI gains are large but heterogeneous across workers, and larger for less experienced workers.
>
> H2: Pass-through of AI-related productivity gains to worker earnings is small, 3 to 7 percent, much lower than the roughly one-half aggregate capture of all productivity gains.
>
> H3: In the U.S. nonfarm business sector, labor captured about half of the productivity gain between 2024 Q1 and 2026 Q3, with a share that fell over time and was negative in the latest four quarters.

H4: AI use is concentrated in large firms and in information and finance, and is low in labor-intensive sectors.

H5: Under plausible bounds on AI's share of productivity growth, AI explains a minority (less than half) of the rise in nonlabor capture.

H6: Entry-level workers in exposed occupations face employment risk that does not appear in aggregate pay statistics.

H1 and H6 are evaluated from published studies, H2 and H4 from published survey tables, H3 from the exact decomposition, and H5 from the consistency analysis.

4. Data

4.1. Sources

Table 1 lists the sources. The aggregate data are from the BLS Productivity and Costs release of 5 November 2026 (preliminary third quarter), which gives indexes of output per hour, hourly compensation, real hourly compensation, unit labor costs, unit nonlabor payments and the output price deflator for the nonfarm business sector from the first quarter of 2024 to the third quarter of 2026, nonfinancial corporate sector indexes, and annual changes (Bureau of Labor Statistics, 2026). The BLS reports that the labor share was 53.0 percent in the third quarter of 2026, the lowest in a series that begins in 1947. The firm-level data are from the Census Bureau's Business Trends and Outlook Survey (BTOS), a biweekly survey of employer firms whose AI supplement asks whether the firm used AI in any business function in the last two weeks; the Census Bureau reported that 19.8 percent of firms did so in the period ending 3 May 2026, with higher rates among large firms (U.S. Census Bureau, 2026; Federal Reserve Bank of Minneapolis, 2026). The question was changed on 17 November 2025 from AI use in producing goods or services to AI use in any business function, which raised measured adoption, so levels before and after are not comparable (Federal Reserve Bank of St. Louis, 2026).

The micro evidence is from published studies. For tasks it uses Brynjolfsson et al. (2025), Noy and Zhang (2023) and Dell'Acqua et al. (2023). For workers it uses Humlum and Vestergaard (2025), which links surveys of 25,000 workers in 11 exposed occupations and 7,000 workplaces to Danish administrative earnings and hours for 2023 and 2024. For entrants it uses the August 2026 update of Brynjolfsson et al. (2026), which covers ADP payroll data through June 2026. The macro bound is from Acemoglu (2025).

4.2. Measures

Productivity π is output per hour. Hourly compensation w and the value-added output price deflator P are used to define the product wage w/P, which measures how much output an hour of labor compensation can buy. The labor share is s = ULC/P up to scale, where ULC is unit labor costs. Because the published indexes do not report the level of the labor share for every quarter, the path of s is derived from the ratio of the ULC index to the deflator and scaled so that the third quarter of 2026 equals the 53.0 percent published by BLS. Unit nonlabor payments cover profits, depreciation, net interest and indirect taxes per unit of output, and are the counterpart of nonlabor capture.

4.3. Data limits

Four limits matter. First, the BLS indexes are published to one decimal place, so growth rates and shares computed from them carry rounding error, which is propagated. Second, the third quarter of 2026 is a preliminary estimate and earlier quarters have been revised, so the numbers will change. Third, aggregate data do not identify the source of productivity growth, so the AI share is not observed. Fourth, the BTOS measure of AI use is a yes-or-no indicator for a firm and says nothing about the intensity of use or the share of workers affected.

5. Methodology

5.1. Capture accounting

Let π be output per hour, w hourly compensation and P the output price. The labor share of output is $s = wL/(PY) = w/(P\pi)$, so that

$$\ln \pi = \ln(w/P) - \ln s.$$

For any window from t0 to t1, the log change in productivity thus splits exactly into the log change in the product wage and the log fall in the labor share. The labor capture share is

$$\kappa_L = \Delta\ln(w/P) / \Delta\ln \pi,$$

and the nonlabor capture share is $\kappa_K = -\Delta\ln s / \Delta\ln \pi = 1 - \kappa_L$. A share of 1 means that gains were fully passed to labor, so that the labor share did not change. A share above 1 means labor gained more than productivity, a negative share that the product wage fell while productivity rose.

5.2. Rounding-error intervals

Each published index is a rounded value x of an unobserved true value x + u with u uniform on (-0.05, 0.05). For each window, 100,000 draws of u are added to the six index values entering the calculation (productivity, hourly compensation and the deflator in two quarters), κ_L is computed for each draw and the 2.5th and 97.5th percentiles are reported (Rubinstein and Kroese, 2017). The intervals reflect rounding only, not revisions, sampling error or measurement error in the underlying data.

5.3. Pass-through cascade

The worker-level pass-through φ_A of AI gains is the ratio of the earnings gain to the productivity gain. For a worker who adopts and saves a share s_t of hours, the implied earnings gain is $\varphi_A s_t$. With s_t = 2.8 percent and φ_A between 3 and 7 percent, this is 0.08 to 0.20 percent of earnings for an adopter, and for an economy in which a share a of workers adopts, a $\varphi_A s_t$. The cascade compares this with the aggregate pass-through κ_L of all productivity gains.

5.4. Consistency bound

Suppose a share ψ of the productivity gain $\Delta\ln \pi$ comes from AI and passes through at φ_A, while the remainder passes through at φ_O. The observed aggregate capture is

$$\kappa_L = (1 - \psi)\, \varphi_O + \psi\, \varphi_A,$$

so that the pass-through of non-AI gains implied by observed data is $\varphi_O = (\kappa_L - \psi\, \varphi_A)/(1 - \psi)$. The AI-attributable nonlabor capture is $\psi(1 - \varphi_A)\, \Delta\ln \pi$, and its share in the total nonlabor capture is

$$\psi(1 - \varphi_A) / (1 - \kappa_L).$$

The identity does not estimate ψ. It shows how the AI share of nonlabor capture depends on it, and the values of φ_O needed to be consistent with the data. A value of ψ is implausible if it requires φ_O to exceed the long-run pass-through of productivity gains to labor, which was close to one when the labor share was stable.

5.5. Bounds on the AI share

The lower bound for ψ uses the macro bound of Acemoglu (2025): at most 0.66 percent additional TFP over ten years, or 0.066 percentage points a year, against observed productivity growth of 2.1 percent over four quarters, a share of 0.03. The upper bound uses adoption arithmetic. If a = 0.40 of workers use generative AI (Bick et al., 2024) and users save 2.8 percent of hours (Humlum and Vestergaard, 2025), the aggregate level gain is 1.1 percent of hours. If it is realised over about three years it equals 0.37 percentage points a year, or 0.18 of annual productivity growth. The upper bound is set at 0.20 to

allow for quality gains. The Monte Carlo draws ψ from U(0.03, 0.20), φ_A from U(0.03, 0.07) and rounding error, with 200,000 draws.

5.6. Reproducibility

All calculations use the published values in Tables 3 and 4 and the parameters stated here, and were performed in Python with NumPy.

6. Results I: From Task Gains to Worker Earnings

6.1. Task-level gains

Table 2 gathers the evidence by level. At the task level, the gains are large and uneven. In the customer-support study, issues resolved per hour rose 14 percent on average and 34 percent for novice and low-skilled agents, with minimal effects for the most experienced (Brynjolfsson et al., 2025). In the writing experiment, time fell by 40 percent and rated quality rose by 18 percent (Noy and Zhang, 2023). The consulting field experiment found gains inside the frontier of AI capability, 12.2 percent more tasks, 25.1 percent faster and 40 percent higher quality, and worse performance outside it (Dell'Acqua et al., 2023). H1 is supported: gains are large, and larger for less experienced workers, but they depend on the fit between task and tool. The consequence for distribution is two-sided. Skill compression may reduce inequality among workers, but if the value of expertise falls, the returns to experience and the bargaining position of skilled workers may also fall.

6.2. Worker-level pass-through

The distance between a task gain and an earnings gain is large. In the Danish data, users reported saving 2.8 percent of work hours, and the study rules out effects on earnings and recorded hours above 1 percent (Humlum and Vestergaard, 2025). Only 3 to 7 percent of productivity gains passed through to earnings. Applying these to the cascade gives an implied earnings gain of 0.08 to 0.20 percent for an adopter, and 0.03 to 0.08 percent for the economy if 40 percent of workers adopt. The aggregate capture of all productivity gains in the BLS data, reported in Section 7, is 52 percent. The AI-specific pass-through is therefore about 7 to 17 times lower than the aggregate average. H2 is supported, with the caveat that the Danish pass-through is measured over a short period when gains may not yet have been bargained over.

Employer behaviour shapes the result. The same study finds that firm-led investments in training and encouragement raised adoption from 47 to 83 percent, so the employer decides who uses the tool. Where employers set the terms of adoption, time savings are more likely to be taken as additional workload or as lower labor needs than as higher pay.

6.3. Where AI is used

Table 6 and Figure 5 show that AI use is concentrated. In the period ending 3 May 2026, 19.8 percent of firms used AI in a business function, compared with 37 percent of firms with 250 or more employees and 32 percent of those with 100 to 249 employees, while the Census Bureau reports less than 20 percent for firms with four or fewer employees. By sector, 39.7 percent of firms in information and 33.9 percent in finance and insurance used AI, against about 14 percent in retail and under 10 percent in labor-intensive sectors such as agriculture, transportation, accommodation and food, and construction (U.S. Census Bureau, 2026; Federal Reserve Bank of Minneapolis, 2026). About 96 percent of firms using AI reported no change in total employment over the previous six months. H4 is supported. If gains are largest where firms are large and capital intensive, and where workers are already highly paid, the first-round distribution is likely to favour owners and the skilled.

7. Results II: Who Captured the Productivity Gain

7.1. The aggregate decomposition

Table 3 and Figures 2 and 3 show the nonfarm business indexes. Between 2024 Q1 and 2026 Q3, output per hour rose 6.6 percent, hourly compensation 11.2 percent, the output price deflator 7.6 percent, unit nonlabor payments 11.6 percent and unit labor costs 4.4 percent. Real hourly compensation, deflated by consumer prices, rose 3.5 percent. In log terms, output per hour rose 6.35 points, the product wage 3.28 points and the labor share fell by 3.07 points, from a derived 54.7 percent to the published 53.0 percent. The labor capture share is therefore 51.7 percent, with a rounding interval of 50.3 to 53.1 percent (Table 4). Nearly half the gain went to nonlabor income. Output growth was mostly productivity: hours rose only 0.7 percent over the period, so 90 percent of the log rise in output came from output per hour.

Over the three years 2023 to 2025 the BLS annual averages tell the same story. Productivity rose 2.0, 3.2 and 2.3 percent, a cumulative 7.7 percent, while real hourly compensation rose 0.1, 2.2 and 1.4 percent, a cumulative 3.7 percent, a ratio of logarithms of 0.50 (Table 5). Productivity growth since the fourth quarter of 2019 has averaged 2.2 percent a year, compared with 1.5 percent in 2007 to 2019 (Bureau of Labor Statistics, 2026), so the acceleration is real, and its distribution is the issue.

7.2. Change over time

The split has worsened. In the four quarters of 2024 labor captured 84 percent of a 2.25-point productivity gain (rounding interval 80 to 89 percent). In 2025 it captured 70 percent of a 2.36-point gain (66 to 74 percent). Between the fourth quarter of 2025 and the third quarter of 2026 productivity rose 1.74 points while the product wage fell 0.27 points, which makes labor capture -16 percent (-20 to -11 percent) and nonlabor capture 116 percent. Figure 4 plots the three windows. The most recent window is short and subject to revision, and the labor share fell most sharply in the second and third quarters of 2026 as unit nonlabor payments jumped (Table 3), so the estimate should be treated as provisional. H3 is supported: labor captured about half of the gain over the whole period, and its share fell over time.

The nonfinancial corporate sector shows the same pattern. Between 2024 Q1 and 2026 Q2, productivity rose 5.8 percent and hourly compensation 8.7 percent, unit labor costs rose 2.7 percent, unit nonlabor costs 9.2 percent and prices 6.7 percent, while unit profits rose 16.1 percent (Table 5).

7.3. Prices and consumers

Consumers did not receive the gains through lower prices. The output price deflator rose 4.1 percent in the four quarters to 2026 Q3, compared with unit labor costs of 2.4 percent and unit nonlabor payments of 6.0 percent. With a labor share of about 0.53, nonlabor payments contributed 2.8 of the 4.1 points of price growth and labor costs 1.3 points, so about two-thirds of recent price growth came from nonlabor payments. This does not show that productivity gains caused price rises, because broad forces affect the deflator, but it shows that there is no evidence in these data of cost savings flowing to buyers.

8. Results III: How Much Could AI Explain?

8.1. Consistency bounds

Table 7 and Figure 6 report the consistency analysis. At $\varphi_A = 0.05$, an AI share ψ of 0.03 implies that AI accounts for 0.18 log points of nonlabor capture, or 5.9 percent of the total, and requires non-AI pass-through of 53 percent. At $\psi = 0.10$ the share is 19.7 percent, at 0.20 it is 39.4 percent and at 0.30 it is 59.2 percent. At $\psi = 0.50$, AI would account for 98.6 percent of nonlabor capture, but the non-AI gains would then have to pass through at 98.7 percent, higher than recent experience, in which the labor share has declined for decades, would suggest.

In the Monte Carlo, with ψ between 0.03 and 0.20 and φ_A between 0.03 and 0.07, the AI share of nonlabor capture has a median of 22.6 percent and a 5th to 95th percentile range of 7.6 to 37.7 percent. Its probability of exceeding 50 percent is zero by construction of the bounds, and the implied non-AI pass-through is 53 to 63 percent. H5 is supported under the stated bounds. AI could be a meaningful contributor, on the order of a fifth of the rise in nonlabor capture, but at least 62 percent of the rise would then need other explanations, among them markups, market concentration, bargaining power or capital deepening. The bound depends on ψ, which is not observed, and a larger AI share would make the result less comfortable.

8.2. Entrants

Aggregate compensation cannot show who bears adjustment costs. Brynjolfsson et al. (2026) report that, through June 2026, employment of workers aged 22 to 25 in AI-exposed occupations was about 19 percent below the level implied by comparison with less-exposed workers, with no such pattern for experienced workers and with adjustment through employment rather than pay. Together with the finding that 96 percent of AI-using firms reported no change in employment, the pattern suggests that AI is affecting hiring at the margin more than it is displacing incumbents. H6 is supported by the cited evidence, which is descriptive, and the paper does not replicate it.

8.3. What the arithmetic implies for the future

The same accounting can be applied forward. Suppose AI raises the level of aggregate productivity by X and passes through to labor at φ. The proportional change in the labor share is -(1 - φ)X, so that with a labor share of 53 percent the absolute change is -0.53(1 - φ)X. If X equals the adoption arithmetic of Section 5.5, 1.12 percent, the labor share falls by 0.56 percentage points at φ = 0.05, by 0.45 points at φ = 0.25 and by 0.28 points at φ = 0.52, the aggregate rate observed in 2024 to 2026, and does not change at φ = 1. If X equals the macro bound of 0.66 percent, the corresponding falls are 0.33, 0.26 and 0.17 points. These numbers are small beside the 1.7-point fall in the derived labor share between 2024 Q1 and 2026 Q3, which is another way of seeing why AI cannot be the main explanation of recent movements. They are also not trivial: a half-point fall in the labor share represents a permanent transfer of about half a percent of output from labor to nonlabor income. The scale of the result depends mainly on φ, and the policy-relevant variable is the pass-through of future gains, which institutions and bargaining can influence.

9. Robustness, Limitations and Validity

Several checks bear on the results. The capture shares are not sensitive to the deflator used. Replacing the product wage with CPI-deflated real hourly compensation, which rose 3.5 percent over the period, gives a labor capture share of 53.5 percent, within two points of the 51.7 percent from the output deflator. The rounding intervals are narrow for the full window (50.3 to 53.1 percent) and wider for short windows, which is expected because the same absolute rounding error is divided by a smaller productivity gain. The qualitative result, that labor's capture falls over time, appears in all three subperiods and in the corporate-sector data. Annual averages, which are less affected by quarterly noise, give a similar ratio of 0.50.

The limitations are considerable. First, the AI share of productivity growth is not observed, and the consistency bounds are not estimates. A larger share would raise the AI contribution, and the upper bound of 0.20 rests on adoption arithmetic that assumes full conversion of time savings into output. Second, productivity and the labor share respond to the business cycle, to energy and trade shocks, to composition and to measurement, and a window of eleven quarters is short. The latest quarter is preliminary and earlier quarters will be revised. Third, the labor share of nonfarm business includes imputed compensation of proprietors and is sensitive to how nonlabor payments such as depreciation

and indirect taxes are treated. Fourth, field studies are not representative: the support agents, writers and consultants studied are in occupations where AI is most useful, and the Danish study covers 11 exposed occupations in one labor market with strong collective bargaining, where pass-through may differ from that in the United States. Fifth, the BTOS yes-or-no question captures any use and not its intensity, and the change in wording in November 2025 prevents long comparisons. Sixth, the study cannot establish causality: it describes the distribution of gains and bounds the AI contribution, and the shift in capture may reflect markups, concentration or bargaining power as much as technology.

10. Discussion and Conclusion

10.1. Discussion

The evidence points to a gap between where gains appear and where they are kept. At the task level, gains are large. At the worker level, only a small fraction passes into earnings, 3 to 7 percent in Denmark, and employers determine how time savings are used. At the firm level, AI use is concentrated among large firms and in information and finance, sectors with high capital intensity and high pay. At the aggregate level, labor captured about half of the productivity gain between early 2024 and late 2026, and its share has fallen over time. Each stage is consistent with a distribution that favours owners of capital and skilled workers, though none proves that AI is the cause. The pattern is not uniform. Gains are larger for novices in some tasks, which could narrow differences in pay among workers within a firm, while the aggregate and firm-level evidence points to a widening gap between labor and capital. These two distributional dimensions, within-labor and between labor and capital, need not move together, and a complete assessment must track both.

The consistency analysis tempers a simple story. If AI accounted for most of recent productivity growth and passed through to workers at 3 to 7 percent, the aggregate capture would be much lower than the 52 percent observed, or the non-AI gains would have to pass through almost fully. Under plausible bounds, AI explains a fifth of the rise in nonlabor capture, with a range of 8 to 38 percent, so that most of the shift needs other explanations. This does not make AI unimportant. A fifth of a 3-point decline in the labor share is 0.7 points, and the share is likely to rise if adoption broadens and if AI-specific pass-through stays low. It means that the claim that AI explains the current distribution of gains is not supported by the available data, and that claims to the contrary need identification beyond aggregate accounting.

The results for entrants are consistent with a pattern in which adjustment happens through hiring. Workers aged 22 to 25 in exposed occupations have lower employment than comparable peers, while firms report no change in total employment and pay data show no clear effect (Brynjolfsson et al., 2026; U.S. Census Bureau, 2026). The costs of AI adoption may therefore fall on those not yet in jobs, who do not appear in pay statistics.

10.2. Implications

For policy, the first implication concerns measurement. Productivity statistics alone are insufficient; the labor share of gains and the product wage should be reported alongside them, with data on adoption intensity and on how firms use time savings. The second concerns institutions. Pass-through is likely to depend on bargaining, training and employer choices, as the Danish evidence on firm-led adoption suggests, so institutions that give workers a voice in how AI is introduced and how its gains are shared may matter for capture. The third concerns entrants: policies for early-career workers, including training and hiring incentives, address the group that evidence suggests carries adjustment costs. The fourth concerns disclosure. Firms that adopt AI at scale could report how time savings are used, in output, hours or headcount, so that workers, investors and policymakers can see where gains go.

For firms, the findings suggest that decisions on how to use time savings, whether to raise output, reduce hours or cut hiring, determine who benefits, and that transparency about them is relevant to trust and retention. For researchers, the priorities are identification of the AI share of productivity growth, with firm-level data on adoption linked to wages and profits, and replication of pass-through estimates in other countries.

10.3. Conclusion

This paper asked who captures the economic gains from workplace AI. Task-level studies show productivity gains of 14 to 40 percent, but Danish administrative data show that only 3 to 7 percent of such gains reach earnings. In the U.S. nonfarm business sector, workers captured 51.7 percent of the 6.35-point rise in output per hour between early 2024 and late 2026, with their share falling from 84 percent in 2024 to 70 percent in 2025 and turning negative in the latest four quarters, while the labor share reached 53.0 percent, the lowest since 1947. AI use is concentrated in large firms and in information and finance. Under plausible bounds AI explains a minority of the rise in nonlabor capture, a median of 23 percent, so that the evidence does not support attributing most of the shift to it.

The limits are those of aggregate, rounded and preliminary data, unobserved AI shares and non-representative field studies. Future work should link firm-level AI adoption to wages, profits and hiring, extend pass-through estimates beyond Denmark, and revisit the decomposition when revised data are available. Until then, the safest conclusion is that productivity gains and prosperity are connected by pass-through, which is low for AI-specific gains and falling for aggregate gains, and that the distribution of what AI produces is still being decided.

Declarations

Data availability: All data are from public sources listed in the reference list, principally the BLS Productivity and Costs release of 5 November 2026 and the Census Bureau Business Trends and Outlook Survey. Derived calculations are reproducible from Tables 3 and 4 and the parameters in Section 5. No new primary data were collected.

Conflicts of interest: The author declares no conflicts of interest.

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Tables for "Productivity Without Prosperity? Who Captures the Economic Gains from Workplace Artificial Intelligence?"

Seven tables from the manuscript. Numbering and notes match the article text.

Table 1. Data sources and derived measures

Source	Content	Use
BLS Productivity and Costs, third quarter 2026, preliminary (USDL 26-1631, 5 November 2026)	Quarterly indexes (2017 = 100) for nonfarm business, 2024 Q1 to 2026 Q3; nonfinancial corporate sector to 2026 Q2; annual changes 2023 to 2025; labor share	Capture decomposition; Tables 3 to 5
U.S. Census Bureau, Business Trends and Outlook Survey (BTOS), AI supplement and biweekly series	Share of employer firms using AI in any business function (period ending 3 May 2026), by size and sector; question changed on 17 November 2025	Adoption; Table 6
Randomised and staggered field studies	Brynjolfsson, Li and Raymond (2025); Noy and Zhang (2023); Dell'Acqua et al. (2023)	Task-level gains; Table 2
Humlum and Vestergaard (2025)	Danish adoption surveys of 25,000 workers in 11 occupations and 7,000 workplaces, linked to administrative earnings and hours, 2023–24	Worker-level time savings and earnings pass-through
Brynjolfsson, Chandar and Chen (2026 update)	ADP payroll records through June 2026; employment of workers aged 22–25 in AI-exposed occupations	Entry-level employment
Acemoglu (2025)	Task-based macroeconomic bound on total factor productivity gains from AI over 10 years	Macro bound
Derived measures	Product wage = hourly compensation ÷ output price deflator; labor share path scaled to the official 53.0% in 2026 Q3; labor capture share = Δln(product wage)/Δln(productivity)	Author's calculations

Notes: Sources are listed in full in the reference list. Index values are published to one decimal, and all derived quantities carry rounding error that is propagated in Table 4.

Table 2. Evidence on gains and their distribution, by level of analysis

Level	Evidence	Estimate	Source
Task	Customer-support agents, staggered rollout (5,179 agents)	Issues resolved per hour +14% on average; +34% for novice and low-skilled agents; minimal for the most experienced	Brynjolfsson et al. (2025)
Task	Randomised writing tasks (453 professionals)	Time −40%; rated quality +18%	Noy and Zhang (2023)
Task	Randomised consulting tasks (758 consultants)	Inside the frontier: 12.2% more tasks, 25.1% faster, 40% higher quality; worse outside it	Dell'Acqua et al. (2023)
Worker	Danish workers in 11 exposed occupations	Reported time savings 2.8% of hours; no earnings or hours effect above 1%; 3–7% of productivity gains passed through to earnings; employer-led adoption raised use from 47% to 83%	Humlum and Vestergaard (2025)
Firm	U.S. employer firms, BTOS	19.8% use AI in a business function (period ending 3 May 2026); 37% of firms with 250+ employees; 96% of users report no change in employment	U.S. Census Bureau (2026)
Macro bound	Task-based model	At most 0.66% increase in TFP over 10 years (0.07% a year); below 0.53% when hard-to-learn tasks are weighted	Acemoglu (2025)
Aggregate outcome	Nonfarm business sector	Productivity +2.2% a year since 2019 Q4 (1.5% in 2007–2019); +2.1% over four quarters to 2026 Q3; labor share 53.0%, lowest since 1947	BLS (2026)
Entrants	Workers aged 22–25 in AI-exposed occupations	Employment about 19% below the level implied by less-exposed peers; no such pattern for experienced workers	Brynjolfsson et al. (2026)

Notes: Estimates are as reported in the sources and are not directly comparable across levels. Source: author's compilation.

Table 3. Nonfarm business sector indexes, 2024 Q1 to 2026 Q3 (2017 = 100 unless stated)

Quarter	Output per hour	Hourly compensation	Real hourly compensation	Unit labor costs	Unit nonlabor payments	Output price deflator	Product wage (2024 Q1 = 100)	Labor share (%, derived)
2024 Q1	114.4	136.4	107.1	119.2	128.6	123.3	100.0	54.7
2024 Q2	115.4	137.8	107.6	119.5	129.9	124.0	100.5	54.5

Quarter	Output per hour	Hourly compensation	Real hourly compensation	Unit labor costs	Unit nonlabor payments	Output price deflator	Product wage (2024 Q1 = 100)	Labor share (%, derived)
2024 Q3	116.4	139.3	108.4	119.7	130.0	124.2	101.4	54.5
2024 Q4	117.0	140.7	108.6	120.3	130.8	124.8	101.9	54.5
2025 Q1	117.0	142.5	109.0	121.8	130.9	125.8	102.4	54.7
2025 Q2	118.2	143.5	109.3	121.5	132.8	126.4	102.6	54.3
2025 Q3	119.5	145.1	109.7	121.5	135.4	127.5	102.9	53.9
2025 Q4	119.8	147.3	110.6	122.9	135.8	128.5	103.6	54.1
2026 Q1	120.2	149.1	111.1	124.0	137.4	129.8	103.8	54.0
2026 Q2	120.9	150.6	110.5	124.6	141.7	132.0	103.1	53.4
2026 Q3	121.9	151.7	110.8	124.4	143.5	132.7	103.3	53.0

Notes: Indexes are from BLS Table 2 (preliminary release of 5 November 2026; recent quarters revised). Product wage = hourly compensation ÷ output price deflator. The labor share path is ULC ÷ deflator scaled so that 2026 Q3 equals the 53.0% reported by BLS. Cumulative change 2024 Q1 to 2026 Q3: output per hour +6.6%, hourly compensation +11.2%, real hourly compensation +3.5%, unit labor costs +4.4%, unit nonlabor payments +11.6%, deflator +7.6%, product wage +3.3%.

Table 4. Capture of productivity gains in the nonfarm business sector

Window	Output per hour (log %)	Product wage (log %)	Fall in labor share (log points)	Labor capture share (%)	Rounding interval for labor share (95%)	Nonlabor capture share (%)
2024 Q1 – 2026 Q3	**6.35**	**3.28**	**3.07**	**51.7**	**50.3 to 53.1**	**48.3**
2024 Q1 – 2024 Q4	2.25	1.89	0.36	84.3	79.8 to 89.0	15.7
2024 Q4 – 2025 Q4	2.36	1.66	0.70	70.3	66.3 to 74.4	29.7
2025 Q4 – 2026 Q3	1.74	−0.27	2.01	−15.7	−20.4 to −11.0	115.7
2024 Q1 – 2025 Q4	4.61	3.56	1.05	77.1		22.9
2024 Q4 – 2026 Q3	4.10	1.39	2.71	33.9		66.1

Notes: Identity ln(productivity) = ln(w/P) − ln(labor share), so labor capture = Δln(w/P)/Δln(productivity) and nonlabor capture is the remainder. Intervals come from 100,000 draws of uniform rounding error (±0.05) added to the published index values. Source: author's calculations from BLS (2026), Table 2.

Table 5. Corporate and annual evidence

Panel A: nonfinancial corporate sector, 2024 Q1 to 2026 Q2	**Change (%)**
Output per hour	+5.8
Hourly compensation	+8.7
Unit labor costs	+2.7
Unit nonlabor costs	+9.2
Output price deflator	+6.7
Unit profits (before tax, with inventory valuation and capital consumption adjustments)	+16.1
Panel B: nonfarm business annual averages (percent change)	**2023 / 2024 / 2025**
Output per hour	2.0 / 3.2 / 2.3
Real hourly compensation	0.1 / 2.2 / 1.4
Hourly compensation	4.3 / 5.2 / 4.2
Unit labor costs	2.2 / 2.0 / 1.9
Cumulative 2023–2025: productivity / real hourly compensation / ratio of logs	7.7 / 3.7 / 0.50
Panel C: 2026 Q3 preliminary	Value
Productivity: quarter (annualised) / four quarters	**3.6% / 2.1%**
Hours worked: quarter / four quarters	0.1% / 0.2%

Panel A: nonfinancial corporate sector, 2024 Q1 to 2026 Q2	Change (%)
Hourly compensation / real hourly compensation: four quarters	4.5% / 1.0%
Unit labor costs: quarter / four quarters	−0.7% / 2.4%
Labor share	53.0% (lowest since 1947)
Productivity growth since 2019 Q4 / 2007–2019 / since 1947	2.2% / 1.5% / 2.2% a year

Notes: Panel A uses BLS Table 6 indexes (unit profits index 166.8 to 193.7). Panel B uses BLS Table C1 (revised). Panel C uses the text and Table A1 of the BLS release. Source: BLS (2026); author's calculations.

Table 6. AI use by U.S. employer firms

Group	Percent using AI in a business function	Note
All firms	19.8	Period ending 3 May 2026; between 17 and 20 percent since December 2025
250 or more employees	37	
100 to 249 employees	32	
Four or fewer employees	below 20	Census publishes a ceiling, not a rate
Information	39.7	
Finance and insurance	33.9	
Retail trade	about 14	
Agriculture, transportation, accommodation and food, construction	below 10	Production-wording series, 2023–25
Used AI in sales and marketing / public relations	about 15 / about 10	April 2026 supplement
AI-using firms reporting no change in total employment over six months	about 96	April 2026 supplement
Firms with 250+ employees vs fewer than 20 (April supplement)	30 vs 17	Different wave and wording

Notes: The BTOS question changed on 17 November 2025 from AI use "in producing goods or services" to "in any business function"; levels before and after are not comparable. A later wave (5–18 October 2026) reported 24.6%, as published by Census and reproduced in secondary sources. Sources: U.S. Census Bureau (2026); Federal Reserve Bank of Minneapolis (2026).

Table 7. Consistency bounds on the AI contribution to capital's capture

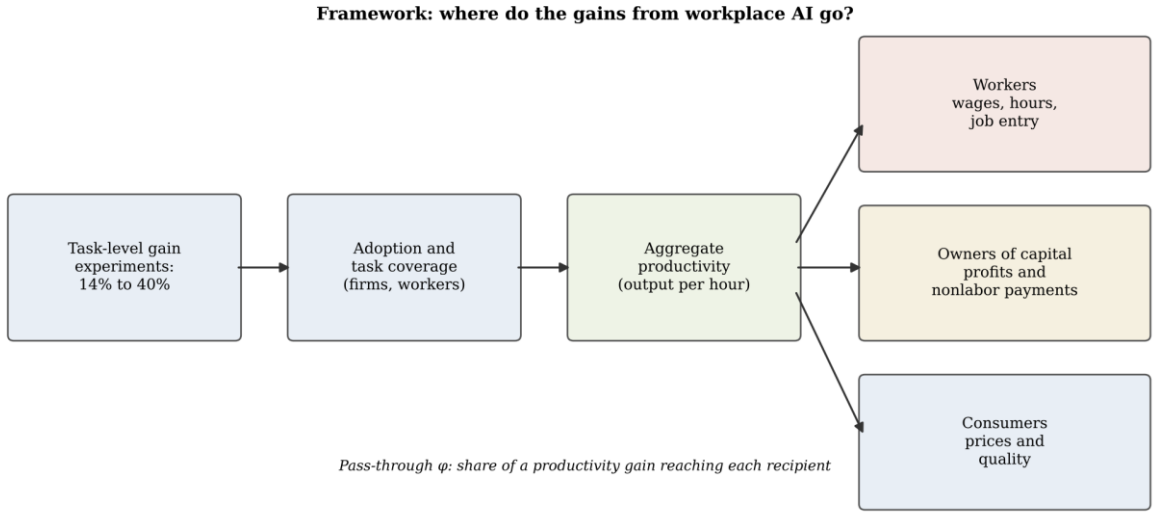
AI share of productivity gain, ψ	Implied non-AI pass-through at φ(AI) = 0.05	AI-attributable capital capture (log points)	Share of total nonlabor capture (%)
0.03	53.3%	0.18	5.9
0.10	57.0%	0.60	19.7
0.20	63.5%	1.21	39.4
0.30	71.9%	1.81	59.2
0.50	98.7%	3.02	98.6
Monte Carlo: ψ ~ U(0.03, 0.20); φ(AI) ~ U(0.03, 0.07); rounding error	**Implied non-AI pass-through: 5th–95th percentile 53.4% to 63.0%**	**Share of nonlabor capture: 5th 7.6%; 25th 14.3%; median 22.6%; 75th 31.0%; 95th 37.7%**	**Probability share exceeds 50%: 0.00**

Notes: Observed aggregate pass-through 0.517 = (1 − ψ) φ(non-AI) + ψ φ(AI). AI-attributable capture = ψ(1 − φ(AI)) × 6.35 log points. ψ bounds: 0.03 (0.066 percentage points a year from Acemoglu, 2025, against 2.1% annual productivity growth) to 0.20 (about 0.4 percentage points a year from the adoption and time-savings arithmetic in Section 5.5). 200,000 draws. Source: author's calculations.

Figures for "Productivity Without Prosperity? Who Captures the Economic Gains from Workplace Artificial Intelligence?"

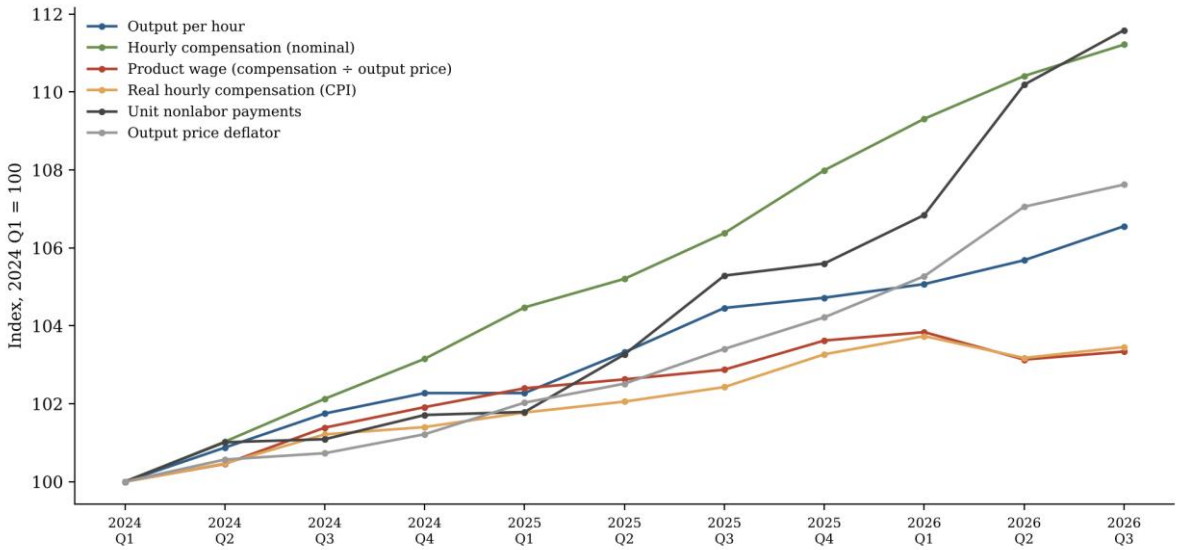
Six figures from the manuscript. Figures 2 to 6 are drawn from published BLS and Census Bureau statistics.

Figure 1. Framework: from task-level gains to the distribution of aggregate gains.



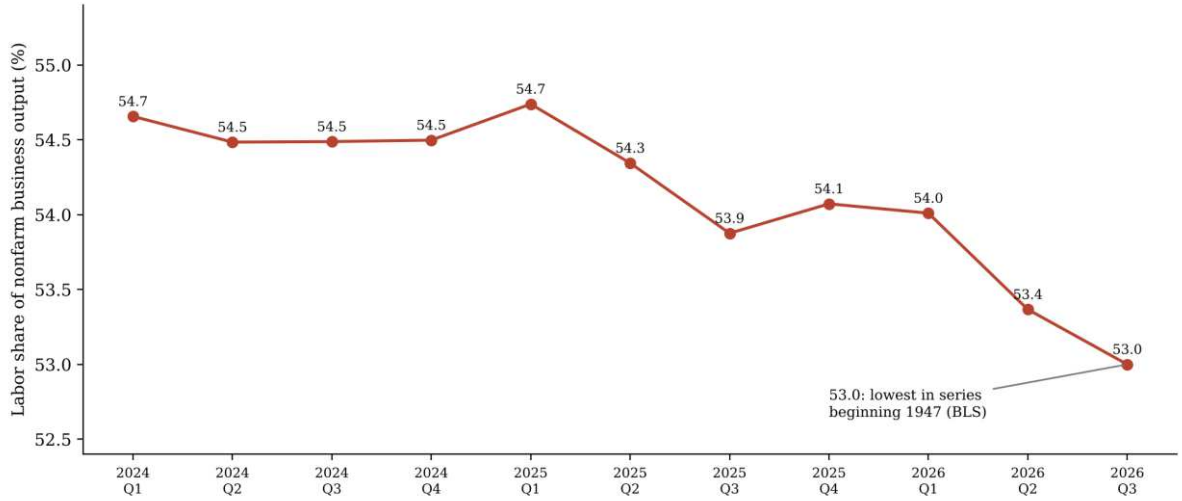
Conceptual framework; not an estimated model.

Figure 2. Output per hour, compensation, nonlabor payments and prices, nonfarm business sector, 2024 Q1 to 2026 Q3 (2024 Q1 = 100).



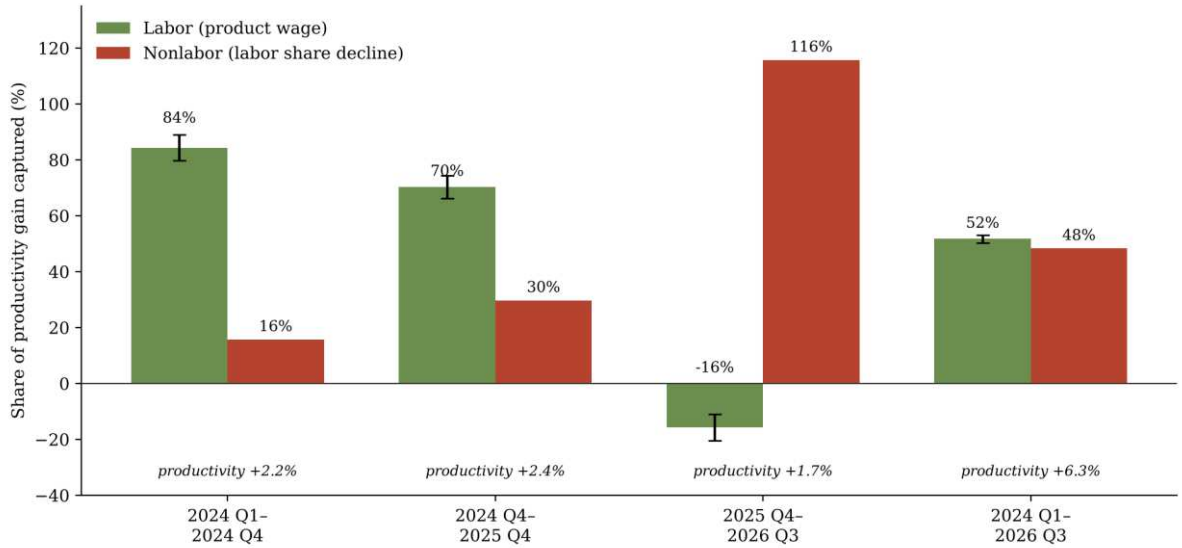
Source: BLS (2026), Table 2; author's calculations. Product wage = hourly compensation ÷ output price deflator.

Figure 3. Labor share of nonfarm business output, 2024 Q1 to 2026 Q3.



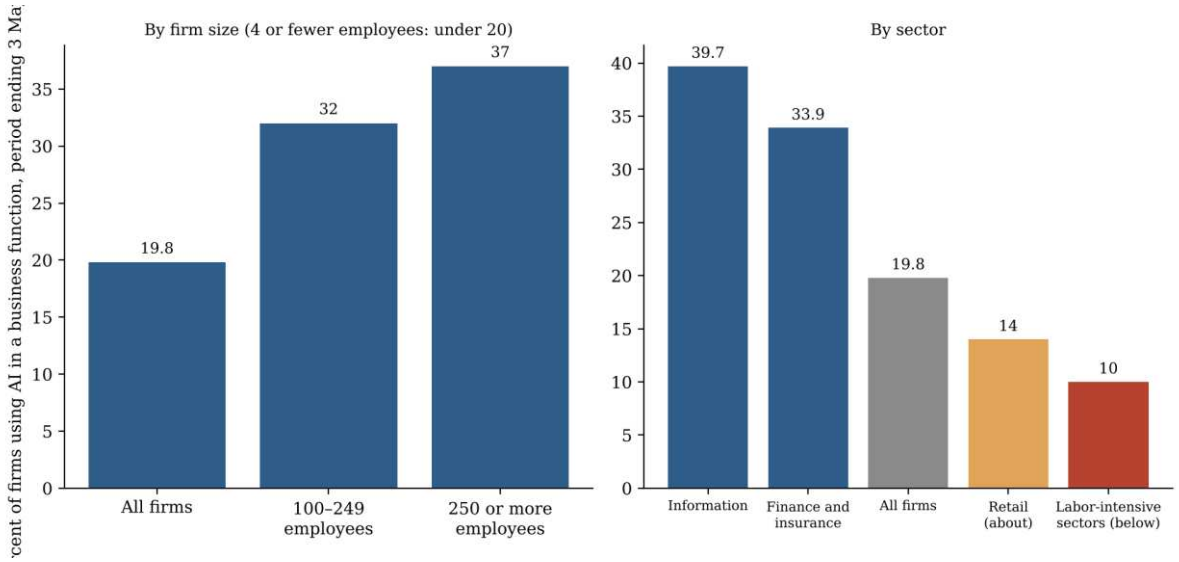
Source: BLS (2026); author's derivation from unit labor costs and the output price deflator, scaled to the published 53.0% in 2026 Q3.

Figure 4. Shares of productivity gains captured by labor and by nonlabor income, by window.



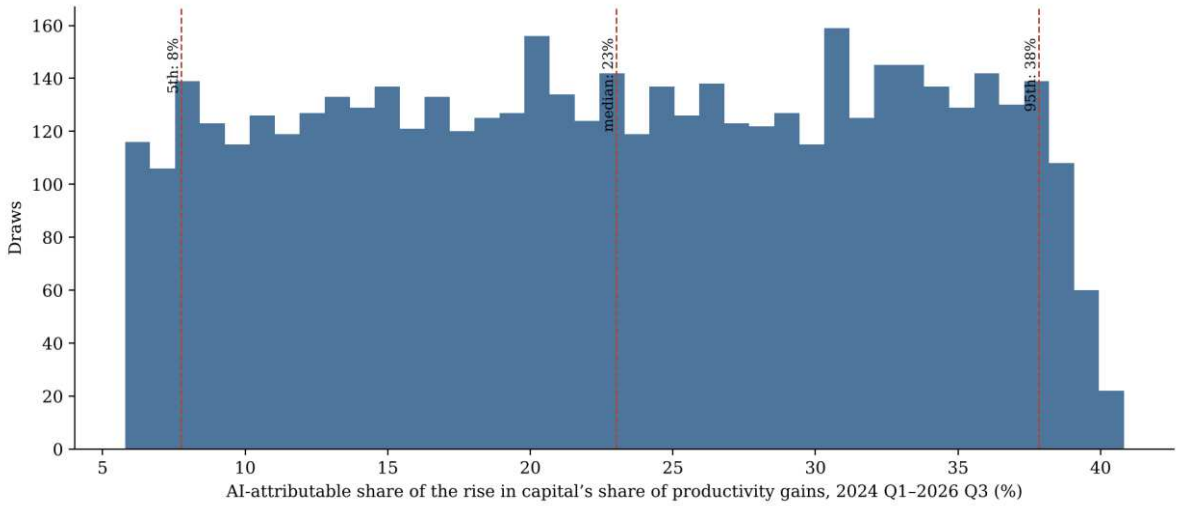
Source: author's calculations from BLS (2026), Table 2. Whiskers are 95% rounding intervals for the labor share. Negative labor capture means the product wage fell while productivity rose.

Figure 5. AI use by firm size and sector, U.S. employer firms, period ending 3 May 2026.



Source: U.S. Census Bureau BTOS (2026) and Federal Reserve Bank of Minneapolis (2026). Retail is approximate; the labor-intensive bar is a ceiling.

Figure 6. Distribution of the AI-attributable share of nonlabor capture under the consistency bounds.



Source: author's calculations (Table 7). ψ ~ U(0.03, 0.20); φ(AI) ~ U(0.03, 0.07); 200,000 draws.