# Artificial Intelligence and Firm Productivity: An Empirical Analysis of Technological Adoption, Labour Market Dynamics and Business Performance

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**Abstract**

In less than a decade, artificial intelligence (AI) has moved from research labs into the day-to-day operations of ordinary firms, yet the evidence on what it does for productivity, jobs and profit is scattered across disciplines and methods. This paper pulls that evidence together. It compares peer-reviewed firm-level, task-level and economy-wide studies published between 2016 and 2026 and asks how AI adoption relates to productivity, labour-market outcomes and business performance. Four patterns stand out. Adoption is concentrated in large, digitally mature firms. Productivity gains are real but modest at the aggregate level, and they are largest for less-experienced workers at the task level. Labor-market effects run mainly through the reallocation of tasks, not through simple headcount cuts. Finally, performance gains tend to flow through product innovation and scale, which also raises concentration. The paper does not introduce a new dataset; it compares published estimates and sets out an estimation strategy that firms and researchers can apply to their own data.

**Keywords:** *artificial intelligence; firm productivity; technology adoption; labour markets; business performance*

## 1. Introduction

Every general-purpose technology arrives with a promise and a delay. Electricity took decades to show up in factory output, and computers famously appeared everywhere except in the productivity statistics (Brynjolfsson, Rock & Syverson, 2021). AI is now taking the same test, only faster. A customer-support agent or a copywriter can start using a language model on the first day, without rebuilding a factory around it.

That speed makes the questions urgent. Does AI adoption actually raise firm productivity? Who inside the firm gains, and who is displaced? And do the gains reach sales and profit, or do they leak away into adoption costs and competition? Researchers have tackled these questions in separate strands: studies of who adopts, studies of what adoption does to output, and studies of what it does to workers. Few read them side by side.

This paper does that. It addresses three research questions:

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1. **RQ1.** Which firms adopt AI, and what organizational conditions make adoption pay off?
2. **RQ2.** How large are the productivity effects of AI at the task, firm and economy level?
3. **RQ3.** How does AI adoption change employment, wages and the skill mix, and how do those changes translate into business performance?

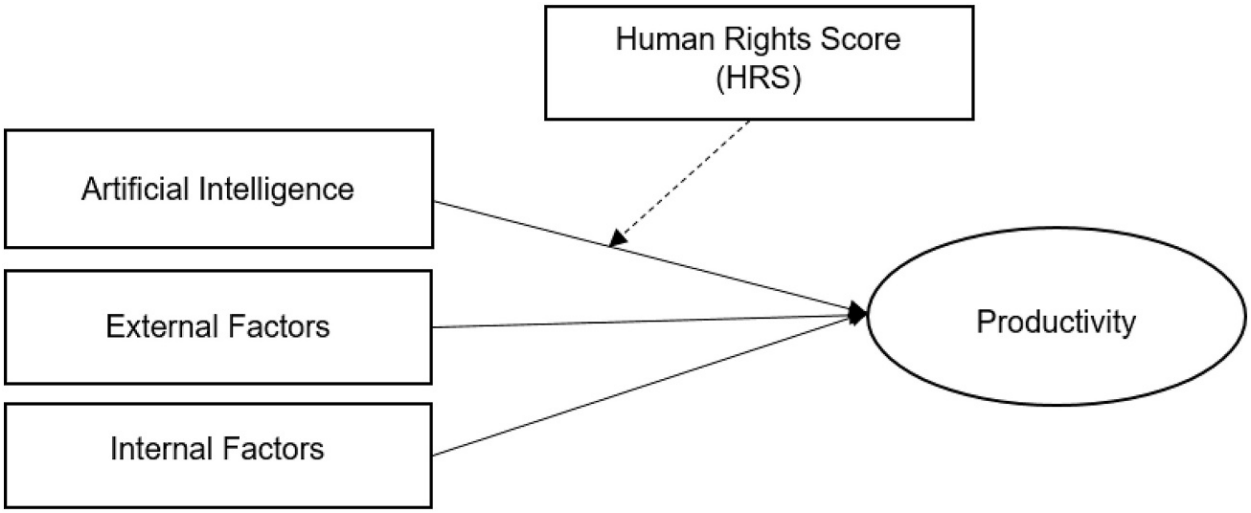


**Fig 1: Conceptual framework**

## 2. Data, Measurement and Empirical Strategy

### 2.1 Evidence base

The comparison draws on peer-reviewed studies published between 2016 and 2026 in economics, management and innovation journals. A study qualified if it (i) measured AI, or a closely related automation technology, at the firm, worker or task level; (ii) reported an outcome in productivity, employment, wages or performance; and (iii) used a design that goes beyond simple correlation, such as an experiment, an instrumental variable or a panel with fixed effects. This is a purposive selection, not an exhaustive systematic review, so it may over-represent well-known journals and high-income countries. Table 1 shows how the main constructs are measured across the literature.

**Table 1. Constructs, typical measures and expected relationships**

| Construct | Typical measures | Typical data source | Expected sign |
|---|---|---|---|
| AI adoption | Use indicator; intensity of AI methods; AI patents; AI job postings | Innovation surveys, business censuses, patent and vacancy data | Explanatory variable |
| Productivity | Sales or value added per worker; total factor productivity | Firm accounts, surveys | Positive |
| Labour outcomes | Headcount, wage bill, skill share, labour share | Payroll and matched employer-employee data | Ambiguous |
| Business performance | Sales growth, market valuation, product launches | Accounts, stock-market data | Positive |

| Construct | Typical measures | Typical data source | Expected sign |
|---|---|---|---|
| Complementary assets | ICT intensity, data capability, training spend | Surveys, accounts | Strengthens effect |

### 2.2 Estimation strategy for firm-level data

For readers with their own firm panel, the baseline specification that most firm-level studies approximate is:

$$\ln Y_{it} = \alpha + \beta\, AI_{it} + \delta\, (AI_{it} \times C_{it}) + \gamma' X_{it} + \mu_i + \tau_t + \varepsilon_{it}$$

Here Y is output per worker for firm i in year t, AI is an adoption indicator or intensity measure, and C captures complementary assets such as ICT capital or training. X holds controls for size, capital and sector, while μ and τ are firm and year effects. H2 predicts $\beta > 0$ and $\delta > 0$.

The hard part is selection. More productive firms are more likely to adopt AI, so a naive estimate overstates its effect. The studies reviewed handle this with instrumental variables (Czarnitzki, Fernández & Rammer, 2023), dynamic panel estimators (Damioli, Van Roy & Vertesy, 2021) or randomised experiments (Brynjolfsson, Li & Raymond, 2025; Noy & Zhang, 2023). When I weigh the results below, I give more trust to the designs that deal with selection directly.

## 3. Results: What the Evidence Shows

### 3.1 Adoption is rare and uneven (RQ1)

Exposure to AI is far wider than actual use. One assessment of large language models suggests that around 80 per cent of US workers could see at least 10 per cent of their tasks affected, and about 19 per cent could see at least half affected (Eloundou et al., 2024). Real adoption is much thinner. In Germany, only around 7 per cent of firms had used any AI method before 2018 (Rammer et al., 2022). US census-based evidence shows that adopters are disproportionately larger firms with strong digital capabilities, clustered in a few places (McElheran et al., 2024). That fits H1 and the J-curve story: the firms that already own the complementary assets are the ones able to use AI well.

### 3.2 Productivity: real, but smaller as you zoom out (RQ2)

Table 2 lines up the main productivity estimates. The pattern is a staircase. Controlled experiments find large effects on specific tasks, firm-level panels find positive but harder-to-size effects, and the macro estimate is small.

**Table 2. Selected estimates of AI and productivity**

| Study | Setting | Design | Headline finding |
|---|---|---|---|
| Noy & Zhang (2023) | 453 college-educated professionals, writing tasks | Randomised experiment | Time taken fell by about 40%; output quality rose by about 18% |
| Brynjolfsson, Li & Raymond (2025) | Over 5,000 customer-support agents at one firm | Staggered rollout | Issues resolved per hour rose by roughly 14–15%, with the largest gains for novices |
| Czarnitzki, Fernández & Rammer (2023) | German firms, survey panel | Instrumental variables and panel | Positive, significant link between AI use and firm productivity, for both adoption and intensity |

| Study | Setting | Design | Headline finding |
|---|---|---|---|
| Damioli, Van Roy & Vertesy (2021) | 5,257 AI-patenting firms worldwide, 2000–2016 | Dynamic panel (GMM-SYS) | AI patenting adds a positive effect on labour productivity beyond other patenting |
| Acemoglu (2025) | Whole economy | Task-based model | TFP gain of no more than about 0.71% over ten years |

Why the staircase? Experiments measure tasks that are easy to learn and easy to score, with workers who know a tool is being tested. Firm-level studies must contend with the fact that stronger firms adopt first. And the macro figure averages the gains over every task, including the many that AI has not touched. None of these is wrong; they answer different questions. The honest reading of H2 is that it is supported on direction and weaker on magnitude.

### 3.3 Labour markets: tasks move before headcount does (RQ3)

The labour evidence is more mixed than either optimists or pessimists admit. Table 3 summarises it.

**Table 3. Selected estimates of automation, AI and labour-market outcomes**

| Study | Setting | Finding |
|---|---|---|
| Acemoglu et al. (2022) | US online job vacancies | AI-exposed establishments cut hiring in non-AI roles; no clear effect on overall employment or wage growth at occupation or industry level |
| Acemoglu & Restrepo (2020) | US commuting zones, industrial robots | One more robot per thousand workers cut the employment-to-population ratio by about 0.2 points and wages by 0.42% |
| Acemoglu, Lelarge & Restrepo (2020) | French firms, robots | Adopters grew and became more productive but lowered their labour share; industry-level employment fell |
| Domini et al. (2021) | French firms, automation spikes | Employment grew after bursts of automation |

Read together, these results say that AI changes what people do inside firms before it changes how many people firms employ. Hiring shifts away from roles AI can perform, and the remaining roles change. Whether total employment falls depends on the market: where adopters win share from rivals, the jobs lost elsewhere can outweigh the jobs gained at the adopter. The experiments add a distributional note, because the biggest gains went to less-experienced workers, which may compress skill premiums inside a firm even as capital gains outpace labour gains across the economy.

### 3.4 Business performance: growth through innovation, concentrated at the top

The link to performance runs through product innovation. US firms that invested in AI saw faster growth in sales, employment and market valuation, and the growth came mainly from new products, not from cost cutting (Babina et al., 2024). The adopters were mostly large firms, which fits H1 and a wider pattern in which a few "superstar" firms capture a rising share of sales while the labour share falls (Autor et al., 2020). In other words, AI looks less like a tide that lifts all firms and more like an advantage that compounds for those already ahead.

### 3.5 Summary against the hypotheses

**Table 4. Assessment of hypotheses**

| Hypothesis | Verdict | Main support | Main caveat |
|---|---|---|---|
| H1: adoption rises with size and digital capability | Supported | McElheran et al. (2024); Babina et al. (2024) | Mostly high-income countries |
| H2: AI raises productivity, more with complements | Partly supported | Czarnitzki et al. (2023); Brynjolfsson et al. (2025) | Effects shrink at firm and macro scale |
| H3: task and skill mix shifts more than headcount; gains run through innovation | Partly supported | Acemoglu et al. (2022); Babina et al. (2024) | Net employment depends on market structure |

## 4. Discussion, Implications and Limitations

### 4.1 What managers can take from this

Three lessons follow. First, treat AI as a complement to the rest of the business, not a standalone purchase. The firms that gain are those with clean data, trained staff and processes that can change. Second, start where the evidence is strongest: well-defined tasks, such as drafting, support and routine analysis, where less-experienced staff gain most. Third, measure honestly. A pilot with a comparison group and a pre-agreed productivity metric will tell a firm far more than an enthusiastic survey of its own staff. Since the J-curve implies a lag, judge the investment over quarters, not weeks.

### 4.2 What policymakers can take from this

If adoption is concentrated in large, digitally mature firms, the gap between leaders and everyone else can widen. Policies that help small and medium-sized firms with data infrastructure, skills and affordable tools matter more than subsidies for firms that would adopt anyway. Because firm-level gains can come at rivals' expense, competition policy and worker transition support deserve as much attention as innovation policy. The macro ceiling in Acemoglu (2025) is also a reminder to plan for modest, steady gains, not a sudden jump in growth.

### 4.3 Limitations

The limits are worth stating plainly. The study selection is purposive, so it may favour prominent journals and positive results. Measures of AI differ widely, from patents to survey questions to job ads, which makes estimates hard to compare directly. Much of the generative-AI evidence comes from one firm or from short lab tasks, and the horizon is short for a technology still being absorbed. Most evidence comes from the United States and Europe, so the results may not transfer to economies with different labour markets and infrastructure. Finally, because I compare published estimates instead of re-estimating them on a common dataset, the verdicts in Table 4 are judgements, not test statistics. A harmonised panel that links AI use, payroll and accounts across countries is the obvious next step.

## 5. Conclusion

AI does raise productivity, but the size of the gain depends on where you look and who is looking. Task-level experiments show large improvements, firm-level studies show positive but smaller ones, and the macro estimates are modest. Adoption is concentrated among large, digitally capable firms, and the labour-market effects show up first as a reshuffling of tasks and hiring patterns, not as a clean rise or fall in jobs. Performance gains flow mainly through product innovation and scale, which may widen the gap between leaders and laggards.

For firms, the practical message is to invest in complements, start with well-defined tasks, and measure with a proper comparison group. For policymakers, it is to widen access, watch competition and support workers through the transition. For researchers, the priority is better data: harmonized, linked and long enough to see the J-curve through to the end.

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