Intangible Capital Meets Skilled Labor: The Implications for Productivity Dynamics*

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Abstract

This paper studies how the interaction between intangible capital and skilled labor shapes firm-level productivity. We proxy skilled labor using firm-level artificial intelligence (AI)-skilled workers and exploit the 2015 release of Google TensorFlow as a plausibly exogenous shock to AI effectiveness. Using a difference-in-differences framework, we show that firms with higher pre-shock AI exposure increase their intangible capital, and these increases translate into higher labor productivity. Moreover, productivity gains are concentrated in large firms, while smaller firms show little response. This heterogeneity implies that the interaction between intangible capital and AI workers contributes to rising productivity dispersion across firms.

Keywords: Productivity, Intangible Capital, Skilled Labor, Artificial Intelligence, Economies of Scale

JEL codes: D22, D24, E22, J24, O33

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1 Introduction

Productivity differences across firms have widened markedly over the past several decades, with an increasing share of productivity growth driven by large firms (Akcigit and Ates, 2023, Andrews et al., 2016, Decker et al., 2018). While existing explanations emphasize market power (Gutiérrez and Philippon, 2017), declining competition, or the role of superstar firms (Autor et al., 2020, Bessen, 2017), the causes and mechanisms underlying the rise in productivity dispersion remain contested.

At the same time, two structural transformations have reshaped the firm production process. First, intangible capital, such as organizational know-how, proprietary knowledge, and data-driven processes, has become an increasingly important input into production. Second, firms have experienced a pronounced rise in demand for skilled labor, particularly workers with advanced computational and analytical expertise. Despite extensive research on each of these trends in isolation, much less is known about how intangible capital and skilled labor interact within firms to shape productivity outcomes.

This paper argues that the interaction between intangible capital and skilled labor constitutes a key yet underexplored mechanism behind rising productivity dispersion. We propose that intangible capital and skilled labor are strongly complementary, in the sense that intangible assets generate productivity gains only when firms possess the skilled workforce required to deploy, adapt, and scale them effectively. Crucially, because intangible capital is scalable and non-rivalrous, this complementarity is amplified by firm size, allowing larger firms to extract disproportionately higher productivity returns from the same technological inputs (Crouzet et al., 2022a, Haskel and Westlake, 2017).

This perspective leads us to three questions. Through what channels do firms leverage intangible capital for productivity improvements? What is the role of skilled labor in this process? How does firm-size heterogeneity shape the magnitude of this synergy? To address these questions, we introduce and formalize a new channel, namely the synergy

between intangible capital and skilled labor, as a partial explanation for the increasing productivity dispersion observed across the firm-size distribution in the U.S. economy.

We approach these questions using firm-level data and a plausibly exogenous shock to the effectiveness of skilled labor. Because firm-level measures of skilled labor are difficult to observe directly, we proxy skilled labor using the firm's share of AI-skilled workers, constructed by Babina et al. (2024). This measure captures highly specialized human capital that is closely linked to data-intensive and computational activities in modern production processes. AI-skilled labor is well suited for our setting because it is closely associated with intangible-intensive activities, such as software development, data analysis, and algorithmic implementation. We interpret intangible capital as an innovation-enabling asset that supports the development, deployment, and scaling of new technologies within firms. In this context, AI-skilled workers represent frontier knowledge that facilitates the effective use of data, software, and algorithmic tools in production and decision-making. Improvements in AI effectiveness therefore affect firm performance not only through efficiency gains, but also by enhancing firms' capacity to generate and exploit intangible capital including innovation-related knowledge.

Following the exogenous variation insight of Rock (2019), we exploit the 2015 release of Google's TensorFlow, an open-source machine learning framework that sharply reduced the cost and complexity of deploying artificial intelligence tools, as a natural experiment that increased the effectiveness of AI-skilled workers. Firms with a larger pre-existing share of AI-skilled labor were therefore differentially exposed to this shock, allowing us to identify the causal impact of improvements in skilled labor effectiveness on intangible investment and productivity.

Using a difference-in-differences (DiD) framework, we document three main findings. First, firms with higher pre-2015 shares of AI-skilled workers exhibit significantly larger increases in intangible capital following the shock, indicating that improvements in AI effectiveness stimulate intangible investment among AI-intensive firms. Second,

these increases translate into higher labor productivity, but only for firms that are already intangible-intensive, suggesting that intangible capital is a necessary input for AI-related productivity gains to materialize. Third, both effects display a pronounced scale dependence: productivity gains are concentrated among large, intangible-rich firms, while smaller firms show little or no response. Dynamic DiD analyses reveal no evidence of differential pre-trends, and an extensive set of robustness checks confirms that the results are not driven by selection, alternative definitions of AI skills, or broader digital transformation.

We also assess the robustness of our causal findings through a series of complementary exercises. We first validate our firm-level results using industry-level data from KLEMS to address concerns related to measurement error and representativeness. We then implement a placebo test to rule out spurious pre-trends and pre-existing differential dynamics. Next, we employ propensity score matching to address potential selection on observables. Furthermore, we extend our benchmark specifications by incorporating state-specific and industry-specific linear time trends to absorb regional and sectoral trends that may be correlated with AI adoption. We also control for firms' exposure to other digital technologies to isolate AI-specific effects from broader digital transformation. Moreover, we examine the sensitivity of our results to the definition of AI skills by using a narrower and more specialized measure of AI talent. Finally, we disaggregate intangible capital into its main components such as knowledge capital, organizational capital, and off-balance-sheet intangibles, and consider R&D expenditures as an alternative innovation input. Across all exercises, the main results remain robust, which reinforces the validity of our empirical strategy and interpretation.

This paper makes three contributions. First, we provide causal firm-level evidence that intangible capital and skilled labor are strongly complementary, and that this complementarity is amplified by firm size. Second, we use AI-skilled labor as a novel and measurable proxy for skilled labor effectiveness and exploit a plausibly exogenous improve-

ment in AI productivity to identify causal effects. Third, our findings offer a technology-based explanation for rising productivity dispersion that complements existing accounts centered on market power and competition.

Our findings have several policy implications. First, policies aimed at fostering AI adoption are likely to be most effective when combined with support for intangible investment, such as data infrastructure, software, and organizational capabilities. Second, because productivity gains from AI effectiveness depend on firms' existing intangible capital and scale, uniform AI subsidies may disproportionately benefit large firms, potentially widening productivity dispersion. This suggests a role for targeted policies that help smaller and intangible-poor firms build the complementary assets needed to benefit from AI technologies. Finally, workforce policies that expand advanced digital and AI-related skills can enhance the returns to intangible investment, strengthening firms' capacity to deploy new technologies and improving aggregate productivity outcomes.

We situate our analysis within the U.S. economy for both data availability and relevance. U.S. datasets offer detailed firm-level information on intangible investment, labor inputs, and productivity. More importantly, our findings speak to broader trends in business dynamism and productivity gaps. While our analysis is U.S.-focused, the mechanisms we uncover are likely relevant elsewhere. Similar patterns of rising intangible capital and skill-biased change have been observed in Europe and other advanced economies (Adler and Siegel, 2019, Andrews et al., 2016, Bartelsman and Wolf, 2017, Van Ark et al., 2013). Thus, our key finding that intangible investment represents a form of technological change that amplifies productivity gaps through its interaction with skilled labor has cross-country applicability. Our work offers a novel explanation for rising productivity dispersion grounded in the evolving nature of capital and labor, and highlights the importance of accounting for their complementarity when evaluating firm dynamics and economic performance.

Related Literature Our paper is related to several strands of literature. The first strand focuses on the declining business dynamism in the U.S. economy. Explanations for this decline include slowing technological diffusion (Akcigit and Ates (2023)), reallocation of factors toward superstar firms (Autor et al. (2020)), implementation and restructuring lags of breakthrough technology (Brynjolfsson et al. (2018)), structural changes in the cost structure due to intangible capital (De Ridder (2024)), and increased market power driven by intangible capital (Crouzet and Eberly (2019)), among others. Our contribution to this strand is to emphasize an additional channel on the synergy between intangible capital and skilled labor, which benefits large firms and leads to an increase in productivity dispersion.

The second strand examines the secular rise of corporate intangible capital over the last five decades (Corrado et al. (2009); Corrado and Hulten (2010); McGrattan and Prescott (2010); Eisfeldt and Papanikolaou (2014); Corrado et al. (2016); Haskel and Westlake (2017); McGrattan (2020)). This literature documents that the accumulation of intangible capital affects several dimensions of firm dynamics, including productivity growth (Corrado et al. (2017), McGrattan (2020)), competition (Ayyagari et al. (2019)), market power (Crouzet and Eberly (2019), De Ridder (2024), Zhang (2019)), markup (Altomonte et al. (2021)), rents (Crouzet and Eberly (2023)), and factor inputs (Chiavari and Goraya (2025)). Using a panel of Italian firms, Arrighetti et al. (2014) examine how intangible assets vary across firms and how this heterogeneity relates to firm characteristics and performance outcomes. They find that the propensity to invest in intangible assets increases with firm size, human capital, and past intangible investment, and that these differences in intangible asset bases are systematically linked to firm-level outcomes. Their results emphasize the importance of accounting for firm heterogeneity in studies of intangible capital and innovation dynamics, highlighting that "one-size-fits-all" interpretations of intangible investment may overlook how capabilities interact with firm characteristics to shape economic performance. Our contribution is to argue that, along with the rising

share of intangible capital in the U.S. economy, the heterogeneity of intangible capital across different firm sizes can partially explain the increasing productivity dispersion.

The third strand highlights the relationship between skilled workers, firm performance, and technological progress, particularly in the context of intangible assets and artificial intelligence. Crouzet et al. (2022b) argue that firms investing heavily in intangible assets, such as R&D and technological innovations, rely on a workforce with specialized skills and knowledge. Ladika et al. (2025) focus on the dynamic interplay between intangible capital and skilled workers, showing that intangible assets result from joint investments by firms and skilled labor. Sun and Xiaolan (2019) propose a dynamic model where investments in intangible capital to boost labor productivity lead to increased deferred wage obligations, reducing the firm's ability to secure debt financing due to employees' limited commitment and potential departure for better opportunities. Piva et al. (2005) provide firm-level evidence that technological change interacts with organizational change to shape skill demand, showing that upskilling in manufacturing is driven not just by technology adoption but by the co-evolution of technology and organizational restructuring, which highlights the importance of firm capabilities and internal organisation in mediating the productivity effects of new technologies. O'Mahony and Vecchi (2009) examine the relationship between intangible assets and firm productivity using company-level data from five advanced economies (the US, UK, Japan, France, and Germany). By combining firm accounts with industry-level information on R&D, intangible investment, and workforce skills, they show that productivity is significantly higher in R&D and skill-intensive industries. The results provide evidence consistent with knowledge spillovers, highlighting the role of intangible capital and skilled labor in shaping productivity performance. Yang (2022) provides firm-level evidence on the effects of artificial intelligence as a general-purpose technology using patent-based measures of AI innovation in Taiwan's electronics industry, and finds that AI technologies are positively associated with both productivity and employment, and that inventing AI technologies substantially reshapes

firms' workforce composition toward more skill-intensive profiles. Engberg et al. (2025) provide worker-level evidence from Germany on how artificial intelligence reshapes the task and skill content of occupations and affects wages. They show that occupations with higher AI exposure face distinct task and skill demands compared to those exposed to robotics. Rammer et al. (2022) analyse the relationship between the use of artificial intelligence and innovation performance using firm-level data from Germany, and show that AI adoption is strongly associated with higher product and process innovation outcomes. Our contribution is to highlight the role of the synergy between intangible capital and AI-skilled labor in the firm-level production and its impact on productivity dispersion across firms.

The final strand investigates the impact of technical change on labor market dynamics. Several papers explore wage dynamics (Katz and Murphy (1992), Acemoglu (1998), Katz et al. (1999), Autor et al. (2008), Violante (2008)), skill-biased technological change (Solow (1957), Greenwood et al. (1997), Krusell et al. (2000), Acemoglu (2002a), Acemoglu (2002b), Aghion et al. (2002), Bresnahan et al. (2002), Hornstein et al. (2005)), and capital-skill complementarity (Griliches (1969), Greenwood and Yorukoglu (1997), Goldin and Katz (1998), Bresnahan et al. (2002), Autor et al. (2003)). Most of these studies focus on the aggregate economy and labor market. However, data limitations often lead to attributing technical change to specific technological trends (e.g., computers, robots, or IT revolution) or unobservable TFP components. Instead, we consider the role of intangible capital in technological change and the structural transformation of the economy. Rather than focusing on specific technological inventions or relying on unobservable TFP components, we observe and quantify the overall trend in intangible capital, emphasizing its role as a new form of technical change in the U.S. economy and its strong association with skilled labor and firm-level productivity.

Layout The paper is organized as follows. Section 2 describes the data, the measurements, and the sample composition. Section 3 presents stylized facts on productivity dispersion, intangible capital, and AI-skilled labor. Section 4 presents the descriptive and causal analyses. Section 5 includes robustness checks. Section 6 concludes by discussing policy implications.

2 Data, Measurement, and Sample Composition

2.1 Data and Measurement

We use the U.S. Compustat database to measure firm-level financial balance sheet variables on an annual basis.

In line with standard procedures in the literature, we exclude financial firms (SIC codes 4900-4999), utilities (SIC codes 6000-6999), and government entities (SIC code 9000 and above). The variables are deflated to constant 1990 U.S. dollars using the Consumer Price Index (CPI).

Measurement of Labor Productivity We measure firm-level labor productivity as sales revenue per employee, a standard approach in the literature using Compustat data (Comin and Philippon 2005; Gutiérrez and Philippon 2016; Autor et al. 2020). A key advantage of this measure is its broad availability and consistency across firms and years. At the same time, Compustat data do not allow for a clean separation between prices and quantities at the firm level, which limits the ideal feasibility of estimating production-function-based productivity measures.

Measurement of Intangible Capital We measure firm-level intangible capital using the Total Q database of Peters and Taylor (2017), which captures both external and internal

channels of intangible investment. External intangible capital reflects the acquisition of existing technologies, knowledge, and organizational capabilities through mergers and acquisitions. Internal intangible capital, by contrast, encompasses two equally central components: knowledge capital and organizational capital. Knowledge capital includes investments in R&D, software, data infrastructure, and related innovation activities that generate new ideas, technologies, and codified knowledge within the firm. Organizational capital captures firm-specific managerial practices, coordination routines, incentive structures, and decision-making processes that govern how this knowledge is integrated into production and scaled across the organization. Both components are largely expensed rather than capitalized under accounting standards and therefore reside off the balance sheet. Therefore, we follow Peters and Taylor (2017) and construct internal intangible capital using a perpetual inventory method, consistent with the view that intangible assets accumulate through sustained investment and learning (Lev and Radhakrishnan 2005; Eisfeldt and Papanikolaou 2014; Ewens et al. 2019).

Measurement of Firm-level AI Workers We use the database constructed by Babina et al. (2024) to measure the firm-level share of AI workers. This database combines employee resume data from Cognism with job posting data from Burning Glass Technologies to create a comprehensive view of firms' engagement with AI talent. The authors develop a novel measure of firms' AI investment by capturing both the stock of AI-skilled workers currently employed by the firm and the flow of AI talent as reflected in job postings. Specifically, the resume data from Cognism provides detailed employee profiles, including educational background, job titles, and self-reported skills, allowing for the identification of existing workers with AI-related expertise. The Burning Glass data, on the other hand, captures the demand side by parsing job advertisements to determine firms' intent to hire workers with AI capabilities.

AI workers are identified based on a curated list of AI-related skills, which are clas-

sified into two categories: *narrow* AI skills that represent highly specialized and directly AI-relevant capabilities, and *broad* AI skills that are more widely applicable and may include peripheral technologies.

2.2 Sample Composition

The final sample used in the main analysis spans 2011–2019. Firm-level measures of AI-skilled labor are largely populated starting in 2010, and we exclude 2010 because it immediately follows the Global Financial Crisis.

Table A.1 presents the firm-level constructed data variables and their descriptions in the Compustat sample. Table A.2 summarizes the sample selection procedure. The final estimation sample comprises 3,960 firms and 27,711 firm–year observations.

Table A.3 reports the distribution of observations across years and industries. The sample is relatively balanced over time, with no single year accounting for a disproportionate share of observations. Industry composition follows the Fama-French 12-industry classification and is broadly diversified. Table A.4 presents summary statistics for the main variables. Firms exhibit substantial heterogeneity in size, investment, productivity, intangible capital, and the share of AI-skilled workers. Table A.5 reports pairwise correlations among key firm characteristics and highlights the joint variation across firm size, investment, productivity, and intangible capital in the sample.

Figure B.1 shows the histogram of the logarithm of intangible capital, indicating substantial heterogeneity across firms. Figure B.2 presents the histogram of the firm-level share of AI workers and reveals a right-skewed distribution with considerable dispersion. Figures B.3 and B.4 report industry-level averages of the logarithm of intangible capital and the share of AI workers across the Fama-French 12 industries, respectively, and document pronounced heterogeneity across industries. Overall, these figures confirm significant variation in intangible capital and AI-skilled labor across firms and in-

dustries, supporting the empirical analysis.

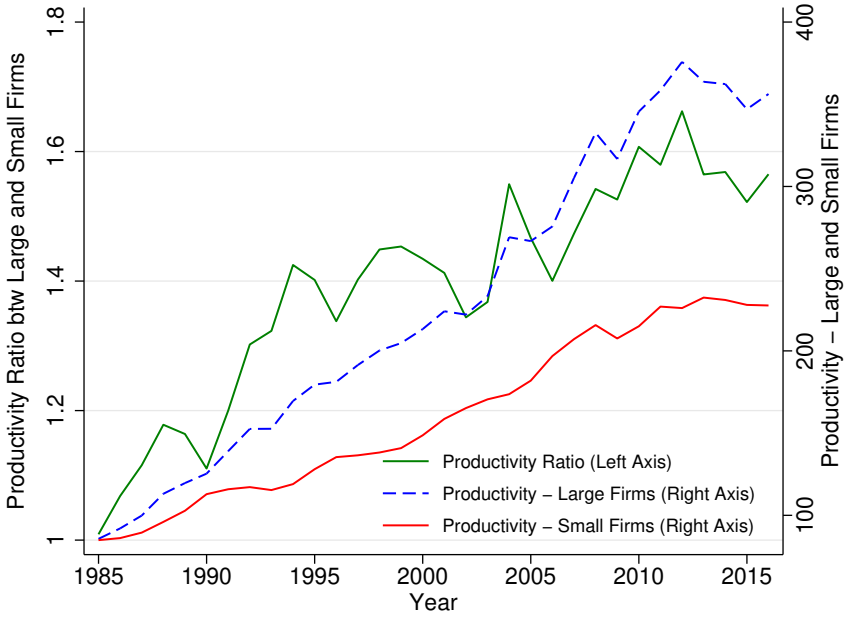
3 Stylized Facts

In this section, we document firm-level stylized facts which present patterns on productivity dispersion, intangible capital, and AI-skilled labor.

Fact 1: Labor productivity gap between large and small firms widens over time in favor of large firms.

Figure 1 shows the average labor productivity ratio between large firms (90th percentile) and small firms (10th percentile) of firm size distribution within each industry and year.

Figure 1: Labor Productivity by Firm Size



Note: The left axis of the figure shows an average labor productivity ratio between large firms and small firms. The right axis of the figure shows the average productivity of large and small firms. Firm size is captured by firm-level total assets. Small firms are the ones which are at the 10th percentile and large firms are the ones which are at the 90th percentile within each year and industry (*NAICS*).

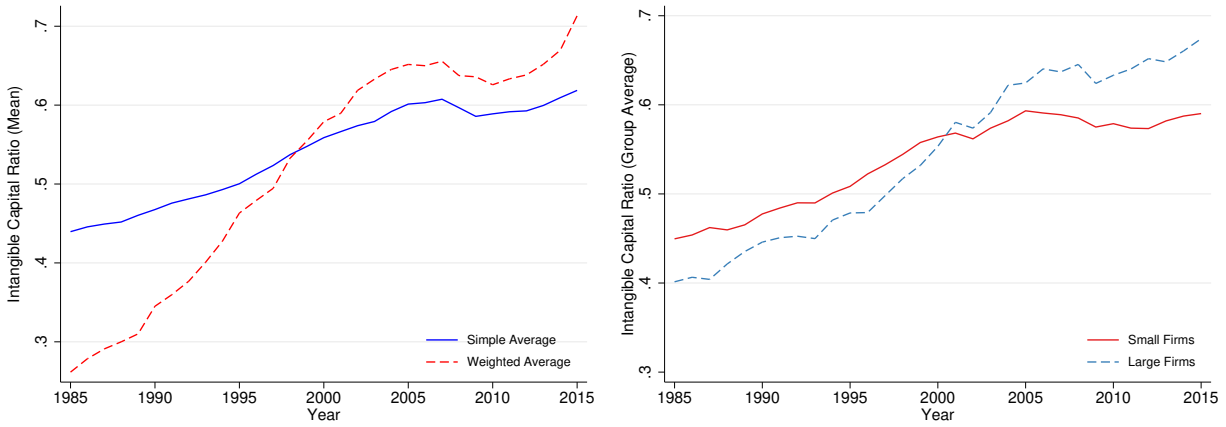
The figure shows that the productivity gap between large and small firms widens

over time. The right axis further indicates that large firms exhibit a steeper upward trend in labor productivity than small firms. This pattern suggests that large firms within an industry are the primary drivers of productivity gains, while smaller firms are unable to catch up. This finding is consistent with evidence in the related literature.

Fact 2: Intangible capital rises in the U.S. economy, which has a heterogeneous pattern across firm size distribution.

Figure 2a shows the simple and sales-weighted averages of the intangible capital ratio across industries over the last three decades. Both measures display a clear upward trend. Specifically, the simple (sales-weighted) average intangible capital ratio increases from about 43% (25%) in the mid-1980s to approximately 61% (71%) by the mid-2010s. Consistent with the related literature, this pattern indicates that the composition of corporate capital in the U.S. economy has become increasingly weighted toward intangible assets over time.

Figure 2: Intangible Capital Ratio by Firm Size



(a) Overall

(b) by Firm Size

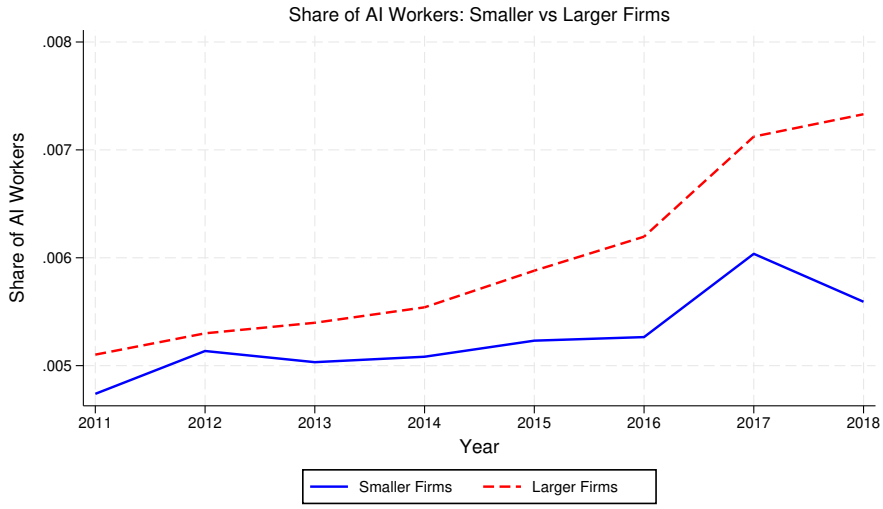
Note: Panel (a) shows the simple and the sales-weighted annual averages of intangible capital ratio in the Compustat. Panel (b) shows the annual average of intangible capital ratio over time for small and large firms. Intangible capital ratio is defined as $\frac{\text{Intangible capital stock}}{\text{Intangible capital stock + Tangible capital stock}}$. Intangible capital stock is based on the perpetual inventory method of Peters and Taylor (2017). Tangible capital stock is the gross plant, property and equipment. For Panel (a), sales weights are calculated within each industry (*NAICS*). For Panel (b), small firms are the ones that are within Quantile 1, where quantiles are constructed based on the firm-level total asset within industry (*NAICS*) and year. Large firms are the ones that are within Quantile 10.

Figure 2b reports the quantile-level annual averages of the intangible capital ratio for small and large firms. Although small firms exhibit relatively higher intangible capital ratios on average in the mid-1980s, large firms rapidly close this gap by the early 2000s and subsequently overtake small firms. This pattern indicates that large firms have accumulated intangible capital disproportionately more than small firms over the past two decades, emphasizing the importance of heterogeneity in intangible capital accumulation across the firm size distribution.

Fact 3: AI-skilled workers disproportinately rise in larger firms.

Figure 3 shows that larger firms have systematically accumulated more AI-skilled workers than smaller firms over time. This persistent size gradient suggests that the accumulation of AI-related human capital is subject to economies of scale, with larger firms being better positioned to attract, retain, and deploy specialized skills. These patterns are consistent with our broader hypothesis that scale plays a central role in shaping firms' ability to build and sustain skilled labor inputs.

Figure 3: Share of AI Workers by Firm Size



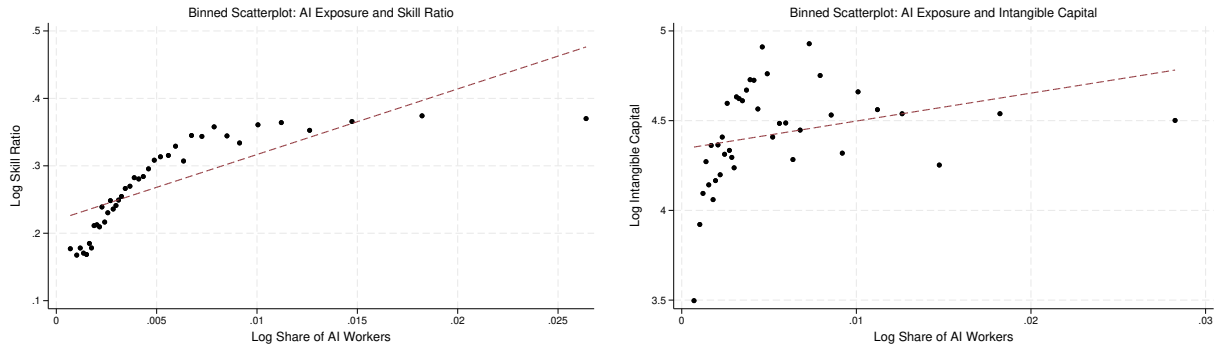
Note: This figure plots the average share of AI workers for larger and smaller firms from 2011 to 2018.

4 Empirical Analysis

4.1 Descriptive Analysis

We first aim to provide suggestive evidence that the share of AI workers serves as a meaningful proxy for firm-level skilled labor. Access to databases that include firm-level skill components is challenging, which limits the variation in skill ratio at the firm level. To capture quasi-variations at the firm-level, we use the Quarterly Workforce Indicators (QWI) from the Longitudinal Employer-Household Dynamics (LEHD) of the U.S. Census Bureau.[1] To measure skill ratio, in line with the related literature, we use the education characteristics variable in QWI and compute the share of workers with a "Bachelor's degree or advanced degree" (labelled as *E4* in the database) within each state, year, industry (4-digit *NAICS*), and firm size. This allows us to capture a disaggregated and detailed measure of skill ratio that vary across industries, states, firm size categories, and years.

Figure 4: Skill Ratio, Intangible Capital, and AI Workers



(a) Skill Ratio vs. AI Workers

(b) Intangible Capital vs. AI Workers

Note: This figure presents binned scatterplots illustrating the relationship between the firm-level share of AI workers and two key variables. Panel (a) plots the log skill ratio against the log share of AI workers, and Panel (b) plots the log of intangible capital against the log share of AI workers.

Figure 4 presents suggestive evidence for the association between the share of AI

[1] For details on the database construction, see Abowd et al. (2009).

workers and two key firm-level outcomes. Figure 4a shows a strong positive relationship between the log share of AI workers and the skill ratio, while Figure 4b reveals a similar association with the logarithm of intangible capital. These binned scatterplots visually reinforce the hypothesis that firms with higher share of AI workers also exhibit higher levels of both skilled labor and intangible capital, consistent with our proposed mechanism of intangible capital-skilled labor complementarity.

Table 1: Association between AI Workers, Skill Labor and Intangible Capital

	(1)	(2)	(3)	(4)	(5)	(6)
	Dependent Variable:					
	Panel A: Skill Ratio					
Share of AI Workers	9.114***	9.254***	1.488***	5.798***	5.955***	0.893***
	(0.690)	(0.695)	(0.245)	(0.588)	(0.593)	(0.222)
Control Variables	No	No	No	Yes	Yes	Yes
Year FE	No	Yes	Yes	No	Yes	Yes
Industry FE	No	No	Yes	No	No	Yes
Adjusted R^2	0.170	0.175	0.756	0.294	0.300	0.775
Observation	15180	15180	15167	14745	14745	14732
	Panel B: Log Intangible Capital					
Share of AI Workers	9.272**	7.005	20.35***	10.45***	10.23***	5.103***
	(4.403)	(4.418)	(4.647)	(1.976)	(1.977)	(1.717)
Control Variables	No	No	No	Yes	Yes	Yes
Year FE	No	Yes	Yes	No	Yes	Yes
Industry FE	No	No	Yes	No	No	Yes
Adjusted R^2	0.001	0.009	0.249	0.714	0.714	0.842
Observation	17599	17599	17587	16266	16266	16253

Note: This table reports regression estimates of the firm-level share of AI workers on two dependent variables: the skill ratio (Panel A) and the logarithm of intangible capital (Panel B). Control variables include the one-year lag of firm-level logarithm of total assets, logarithm of R&D expenditures, logarithm of capital expenditures, the cash-to-asset ratio, markup, and the dividend-to-asset ratio. Since the skill ratio dependent variable is not measured at the firm level, we cannot include firm fixed effects in Panel A. For consistency, firm fixed effects are also excluded from Panel B. Standard errors (in parentheses) are clustered at the firm level. * $p < .10$, ** $p < .05$, *** $p < .01$.

To formally quantify these relationships, Table 1 reports the regression estimates of AI worker share on the skill ratio (Panel A) and intangible capital (Panel B), across several specifications. The results are robust across controls and fixed effects, consistently showing that an increase in the share of AI workers is positively and significantly associated with both higher skill ratios and greater intangible capital accumulation. Specifically, in the most comprehensive specification (column 6), a one percentage point increase in the AI worker share is associated with a 0.89 percentage point increase in the skill ratio and a 5.10% increase in intangible capital, respectively. These findings validate the use of AI worker share as a proxy for skilled labor and provide strong empirical support for the complementarity channel we emphasize. The positive association we document between AI workers and the skilled labor ratio is consistent with the evidence in Yang (2022), who shows that inventing AI technologies substantially reshapes firms' workforce composition toward more skill-intensive profiles.

4.2 Causal Analysis

In this section, we exploit an exogenous shock to the effectiveness of AI workers to investigate the synergy between intangible capital and skilled labor.

4.2.1 Difference-in-Differences

We now turn to establishing a causal claim for the mechanism we propose. Specifically, we investigate whether greater effectiveness of AI workers leads to higher accumulation of intangible capital and improved labor productivity. To do so, we exploit the 2015 release of Google TensorFlow, a widely adopted open-source machine learning platform, as an exogenous shock that substantially lowered the cost and technical barriers to implementing AI technologies. This technological breakthrough, as highlighted by Rock (2019), enabled firms to leverage their existing AI workforce more productively.

Discussion on the Google TensorFlow Shock Following Rock (2019), we exploit the 2015 release of Google TensorFlow as a plausibly exogenous shock to the effectiveness of AI-skilled workers. TensorFlow is an open-source, general-purpose machine learning framework that substantially reduced the technical complexity and cost of deploying advanced AI models. Its release was not targeted at specific firms, industries, or regions, but instead represented a broad technological improvement that enhanced the productivity of existing AI expertise economy-wide. A growing body of work highlights the TensorFlow as a major inflection point in the diffusion of artificial intelligence. Using patent-level data, Chen et al. (2024) show that the economic value of AI-related innovations rises markedly after TensorFlow becomes publicly available, with particularly strong effects in application-oriented sectors where shared machine-learning frameworks enhance knowledge spillovers. Related evidence from Chen et al. (2025) documents a pronounced post-2015 surge in firms' demand for AI-related skills such that references to TensorFlow are virtually nonexistent prior to 2015 (only a single mention between 2010 and 2015) but increase sharply to more than 26,000 mentions between 2016 and 2021. Leveraging the timing of TensorFlow's release in a difference-in-differences design, they further provide causal evidence that AI adoption leads to improvements in climate-related innovation, environmental management, and firms' disclosure practices.

In our context, this shock is expected to raise the marginal product of AI-skilled workers by facilitating faster model development, easier implementation, and more efficient experimentation. Because TensorFlow primarily improves the effectiveness of pre-existing AI talent, rather than inducing immediate changes in firm size, capital structure, or workforce composition, firms with higher pre-2015 shares of AI-skilled workers are plausibly more exposed to the shock. This feature motivates the use of pre-treatment AI worker intensity as a measure of firm-level exposure.

Importantly, we do not interpret the TensorFlow release as generating a purely mechanical increase in labor productivity. If the shock operated solely through task automa-

tion, one would expect relatively uniform effects across firms. Instead, this framework suggests that any productivity response should depend on firms' ability to deploy AI technologies within their existing production structure. In particular, intangible capital such as data assets, software, and organizational infrastructure provides the platform through which improvements in AI effectiveness can be integrated into firm operations. This reasoning motivates our focus on heterogeneity across firms with different levels of intangible capital and scale in the empirical analysis.

A potential concern is that firms with higher pre-2015 shares of AI-skilled workers may differ systematically from other firms along observable characteristics, raising the possibility of selection into AI workers. While this concern does not undermine the interpretation of TensorFlow as an economy-wide improvement in AI effectiveness, it motivates additional empirical safeguards. To address potential selection on observables, we complement our baseline analysis with propensity score matching in the robustness section, comparing firms with similar pre-treatment characteristics.

Empirical Strategy To capture firm-level exposure to the TensorFlow shock, we use the pre-treatment share of AI workers in 2014 as a proxy for a firm's ex-ante AI intensity. While this exposure measure may be correlated with other firm characteristics, our empirical strategy explicitly addresses these concerns. First, we control for a rich set of time-varying firm characteristics, which absorb many observable sources of heterogeneity correlated with AI adoption. Second, we include firm fixed effects, thereby exploiting within-firm variation over time and netting out all time-invariant firm characteristics, such as managerial quality, corporate culture, or persistent differences in technology orientation. As a result, identification comes from differential post-TensorFlow changes in firm outcomes between firms with higher versus lower pre-2014 AI intensity, rather than from cross-sectional differences in levels. Third, as an additional robustness check, we implement a propensity score matching procedure that pairs AI-exposed firms with ob-

servationally similar control firms based on pre-treatment characteristics.

We estimate the following baseline specification:

$$Y_{it} = \beta_1 \text{Post}_t \times \text{Share of AI Workers}_{i,2014} + X'_{it-1}\gamma + \lambda_t + \theta_s + \delta_j + \mu_i + \varepsilon_{it} \tag{1}$$

where Y_{it} denotes the outcome of interest for firm i in year t, measured by either the logarithm of intangible capital or the logarithm of labor productivity. We normalize the logarithm of intangible capital by one-period lagged total assets to construct an intensity measure relative to firm size. The indicator variable Post_t equals one for years following the release of TensorFlow (i.e., $t \geq 2015$), and zero otherwise. Share of AI $\text{Workers}_{i,2014}$ represents the firm's share of AI-related workers in 2014 and proxies for the firm's potential to benefit from TensorFlow's release. The interaction term $\text{Post}_t \times$ Share of AI $\text{Workers}_{i,2014}$ identifies the average treatment effect of the exogenous improvement in AI effectiveness.

The vector X_{it-1} includes one-year lagged control variables: the logarithm of total assets, the logarithm of R&D expenditures, the logarithm of capital expenditures, the cash-to-asset ratio, markup, and the dividend-to-asset ratio. We measure firm-level markup by following De Loecker et al. (2020), and explicitly control it to account for the possibility that market power constitutes an alternative channel through which technological change and intangible capital may affect productivity. By conditioning on markups, we ensure that the estimated effects of AI effectiveness and intangible capital are not mechanically driven by changes in market power, but instead reflect improvements in firms' ability to deploy knowledge and organizational capital in production. Year fixed effects (λ_t) control for macroeconomic shocks; industry fixed effects (θ_s) account for time-invariant differences across sectors; state fixed effects (δ_j) absorb regional variation across firm locations; and firm fixed effects (μ_i) control for time-invariant unobservable heterogeneity at the firm level. Standard errors are clustered at the firm level.

Identification Assumptions The validity of our causal interpretation hinges on several identification assumptions. First, the key assumption in our difference-in-differences design is that, absent the TensorFlow shock, firms with varying pre-treatment shares of AI workers would have followed parallel trends in intangible capital and labor productivity. We provide support for this assumption through dynamic DiD analyses, which reveal no differential pre-trends across firms with different AI intensity levels prior to 2015. Second, we assume that the 2015 release of Google TensorFlow represents a plausibly exogenous and industry-wide improvement in AI effectiveness that differentially benefits firms based on their ex-ante AI workforce, but is otherwise unrelated to concurrent shocks to productivity or intangible investment. This assumption is supported by the timing and general-purpose nature of TensorFlow's release, which was not targeted at specific sectors or firm types. Third, our use of firm, industry, year, and state fixed effects helps control for unobserved heterogeneity and time-varying confounders at multiple levels. Taken together, these assumptions strengthen the interpretation that the interaction between TensorFlow's release and AI workforce intensity captures a causal effect on firm-level outcomes.

Causal Estimates Table 2 presents the baseline difference-in-differences (DiD) results that estimate the impact of the TensorFlow shock on firm-level intangible capital. Across a range of specifications, we find consistent evidence that firms with higher ex-ante AI worker share experienced greater intangible capital accumulation following the release of TensorFlow. In the most saturated specification (Column 4), which includes firm, industry, year, and state fixed effects, the coefficient on the interaction term is positive and statistically significant at the 1% level, indicating that a one percentage point higher share of AI workers in 2014 is associated with an 8.07% increase in intangible capital after 2015. This result highlights our interpretation that improved AI effectiveness translates into greater investment in intangible capital among firms that were already AI-intensive prior

to the shock. The estimated effects are also economically meaningful. The average firm in 2014 employs approximately 0.3 percent of its workforce in AI-related occupations. Combining this baseline exposure with the coefficient in Column (4) implies that the TensorFlow shock increased intangible capital by roughly 2.4 percent for the average firm. Given that the mean level of intangible capital in our sample is approximately $120 million, this corresponds to an increase of about $3 million in intangible capital.

Table 2: DiD Estimates: AI Workers and Intangible Capital

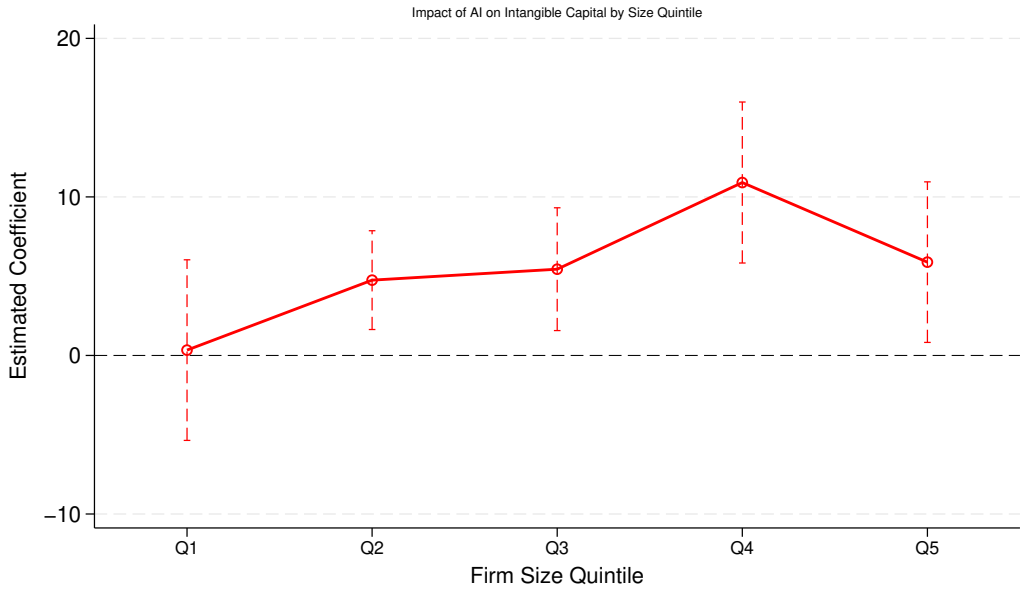
	(1)	(2)	(3)	(4)
	Log Intangible	Log Intangible	Log Intangible	Log Intangible
Post × Share of AI Workers$_{2014}$	8.222***	7.792***	7.792***	8.067***
	(1.480)	(1.464)	(1.475)	(1.558)
Control Variables	Yes	Yes	Yes	Yes
Year FE	No	Yes	Yes	Yes
Industry FE	No	No	Yes	Yes
State FE	No	No	No	Yes
Firm FE	Yes	Yes	Yes	Yes
Adjusted R^2	0.945	0.946	0.945	0.949
Observation	32920	32920	32920	27712

Note: This table reports difference-in-differences regression estimates of the interaction between the post-TensorFlow indicator and the firm-level share of AI workers in 2014 on the logarithm of intangible capital. Control variables include the one-year lag of firm-level logarithm of total assets, logarithm of R&D expenditures, logarithm of capital expenditures, the cash-to-asset ratio, markup, and the dividend-to-asset ratio. All regressions include various combinations of year, industry, state, and firm fixed effects as indicated in each specification. Standard errors (in parentheses) are clustered at the firm level. * $p < .10$, ** $p < .05$, *** $p < .01$.

Figure 5 complements this result by plotting the DiD coefficient across firm size quintiles. The figure shows that the impact of TensorFlow on intangible capital is heterogeneous across the firm-size distribution. Notably, the treatment effect is close to zero for the smallest quintile (Q1), but becomes increasingly positive and significant as firm size increases. It suggests that larger firms are more capable of leveraging AI-capable labor in ways that amplify intangible capital accumulation. This size gradient is consistent with

our hypothesis that economies of scale amplify the synergy between AI-driven skilled labor and intangible investment.

Figure 5: DiD Estimates by Firm Size Quintiles: AI Workers and Intangible Capital



Note: This figure plots the estimated coefficients from difference-in-differences regressions of the impact of the TensorFlow shock on the logarithm of intangible capital, stratified by firm size quintiles. Firm size quintiles are constructed within each year and industry based on the distribution of total assets. The plotted coefficients correspond to the interaction between the post-TensorFlow indicator and the pre-2014 share of AI workers within each firm size quintile. Control variables include the one-year lag of the firm-level logarithm of total assets, logarithm of R&D expenditures, logarithm of capital expenditures, the cash-to-asset ratio, markup, and the dividend-to-asset ratio. The specification includes year, industry, state, and firm fixed effects. Standard errors are clustered at the firm level. Confidence intervals are shown at the 90% level.

Table 3 presents our difference-in-differences (DiD) estimates of the impact of the TensorFlow shock on firm-level labor productivity. Columns (1)–(5) show results from baseline specifications that include various combinations of fixed effects and control variables. In these models, the interaction term between the post-TensorFlow indicator and the pre-treatment share of AI workers captures the average effect of improved AI effectiveness on labor productivity. While the estimated coefficients vary across specifications, we observe that the interaction term becomes positive and statistically significant once firm-level controls, year, industry, state, and firm fixed effects are included. This pattern suggests that firms with higher pre-existing AI workforce shares tend to benefit more from the increased effectiveness of AI technologies following the TensorFlow release. In Column

(5), we augment the baseline model by introducing an interaction between the TensorFlow shock and lagged intangible capital, allowing us to directly test the complementarity channel. The coefficient on the triple interaction term (Post $\times$ Share of AI Workers$_{2014}$ $\times$ Lagged Intangible Capital) is positive and highly significant. This result implies that the labor productivity gains from the TensorFlow shock are concentrated among firms that are both AI-intensive and intangible-capital intensive. Quantitatively, a one percentage point increase in AI worker share is associated with a 6.10% increase in labor productivity for firms with one standard deviation higher intangible capital. This finding provides strong causal evidence for the synergy between AI-skilled labor and intangible capital in driving productivity improvements.

Table 3: DiD Estimates: Labor Productivity, AI Workers, and Intangible Capital

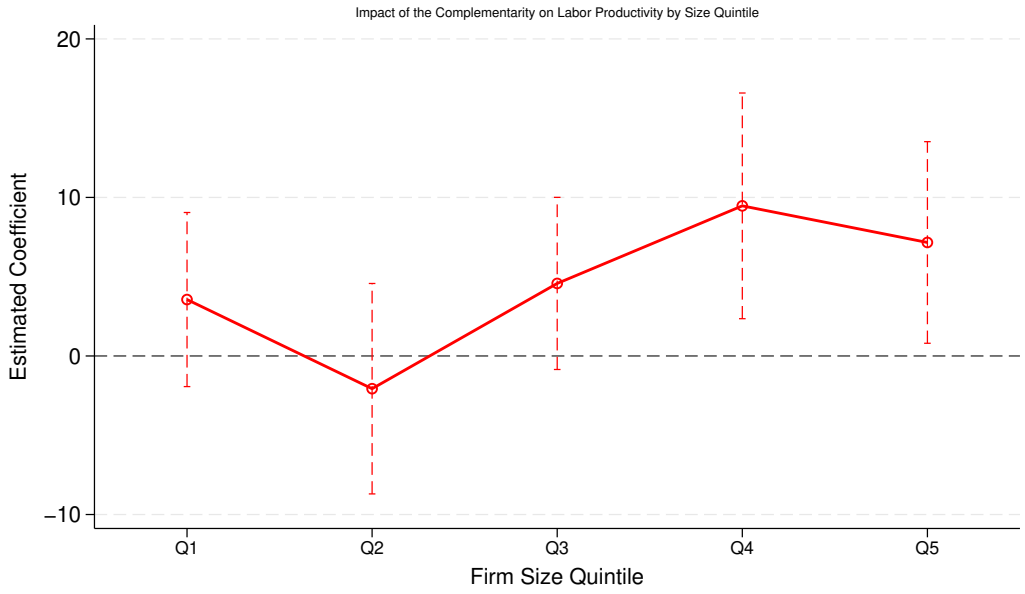
	(1)	(2)	(3)	(4)	(5)
	Log Productivity	Log Productivity	Log Productivity	Log Productivity	Log Productivity
Post $\times$ Share of AI Workers$_{2014}$	3.639***	3.633***	3.633***	5.269***	4.440***
	(1.249)	(1.257)	(1.267)	(1.319)	(1.362)
Post $\times$ Share of AI Workers$_{2014}$ $\times$ L.Intangible Capital					6.097***
					(1.822)
Control Variables	Yes	Yes	Yes	Yes	Yes
Year FE	No	Yes	Yes	Yes	Yes
Industry FE	No	No	Yes	Yes	Yes
State FE	No	No	No	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes
Adjusted R^2	0.951	0.951	0.950	0.954	0.954
Observation	32919	32919	32919	27711	27711

Note: This table reports difference-in-differences regression estimates of the interaction between the post-TensorFlow indicator and the firm-level share of AI workers in 2014 on the logarithm of labor productivity. Column (7) includes a triple interaction term with the lagged intangible capital ratio to capture the complementarity effect. Control variables include the one-year lag of firm-level logarithm of total assets, logarithm of R&D expenditures, logarithm of capital expenditures, the cash-to-asset ratio, markup, and the dividend-to-asset ratio. All regressions include various combinations of year, industry, state, and firm fixed effects as indicated in each specification. Standard errors (in parentheses) are clustered at the firm level. * $p < .10$, ** $p < .05$, *** $p < .01$.

The productivity effects are also economically meaningful. Evaluated at the sample mean, where labor productivity is approximately \$49,000 per worker, the estimates imply that an average firm with a 0.3 percentage point share of AI workers in 2014 experiences a post-TensorFlow productivity increase of roughly 10 percent, corresponding to about \$5,000 higher sales per worker. A one-standard-deviation increase in AI exposure raises labor productivity by nearly 16 percent, or approximately \$7,700 per worker. Turning to

the triple-interaction specification, the implied effect of a 1 percentage point higher AI worker share is about 23 log points when evaluated at the 25th percentile of intangible capital, and rises to about 44 log points at the 75th percentile. Translating these effects into economic magnitudes using the sample mean labor productivity, the average 2014 AI exposure corresponds to an increase of approximately $3,400 in sales per worker for low-intangible firms (25th percentile) and about $6,400 for high-intangible firms (75th percentile).

Figure 6: DiD Estimates by Firm Size Quintiles: Labor Productivity, AI Workers, and Intangible Capital



Note: This figure plots the estimated coefficients from difference-in-differences regressions of the impact of the TensorFlow shock on the logarithm of labor productivity, stratified by firm size quintiles. Firm size quintiles are constructed within each year and industry based on the distribution of total assets. The plotted coefficients correspond to the triple interaction term between the post-TensorFlow indicator, the pre-2014 share of AI workers, and the lagged intangible capital ratio, estimated within each firm size quintile. Control variables include the one-year lag of the firm-level logarithm of total assets, logarithm of R&D expenditures, logarithm of capital expenditures, the cash-to-asset ratio, markup, and the dividend-to-asset ratio. The specification includes year, industry, state, and firm fixed effects. Standard errors are clustered at the firm level. Confidence intervals are shown at the 90% level.

Figure 6 reinforces this pattern using a stratified DiD approach by firm size quintiles. The plot shows that productivity gains are concentrated in larger firms. While the treatment effect is near zero and statistically insignificant, it becomes increasingly positive and economically meaningful moving toward the upper end of the size distribution. These

findings confirm that the synergy between AI-skilled labor and intangible capital yields the strongest productivity returns in larger firms.

4.2.2 Dynamic Difference-in-Differences

To further explore the dynamics underlying our causal claims, we implement a dynamic DiD design. This approach allows us to visualize the evolution of treatment effects over time and assess the validity of the parallel trends assumption. Specifically, we estimate a dynamic difference-in-differences specification of the following form:

$$Y_{it} = \sum_{\tau \neq -1} \beta_\tau \left(\mathbb{1}\{t = \tau\} \times \text{Share of AI Workers}_{i,2014} \right) + X'_{it-1}\gamma + \lambda_t + \theta_s + \delta_j + \mu_i + \varepsilon_{it} \quad (2)$$

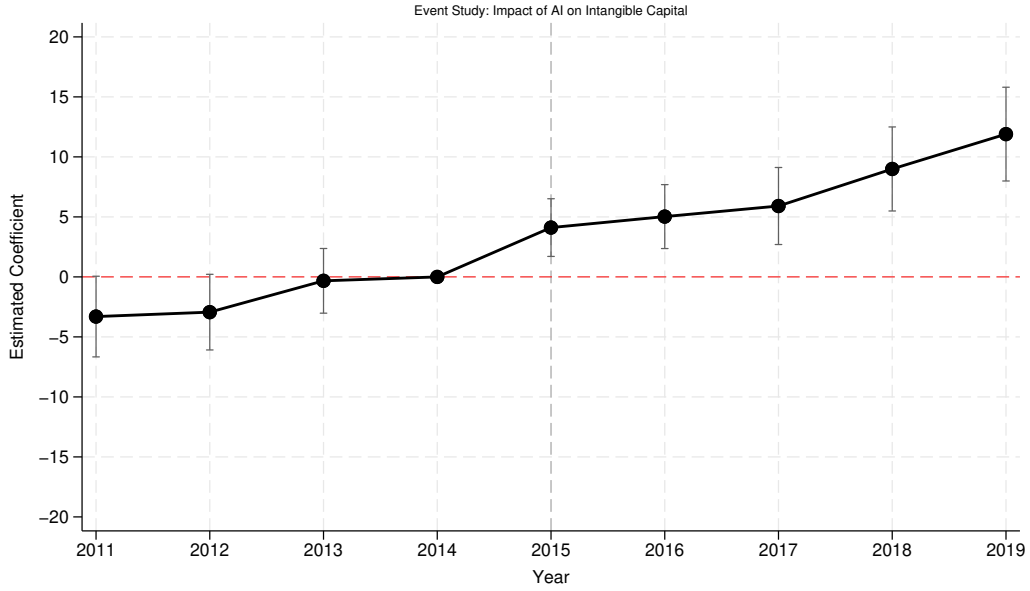
where the dependent variable Y_{it} represents firm i's outcome in year t, measured by either the logarithm of labor productivity or the logarithm of intangible capital. The variable Share of AI Workers$_{i,2014}$ denotes the firm's pre-treatment share of AI-related workers and serves as a continuous proxy for its ex-ante exposure to the 2015 release of Google TensorFlow. This specification enables us to trace the differential trajectory of outcomes across firms with varying AI intensity, before and after the shock.

The terms $\mathbb{1}\{t = \tau\}$ are event-time indicators, where $\tau = 0$ denotes the year of TensorFlow's release (2015), and $\tau = -1$ serves as the omitted baseline category. The vector X_{it-1} includes lagged firm-level control variables: the logarithm of total assets, the logarithm of R&D expenditures, the logarithm of capital expenditures, the cash-to-asset ratio, markup, and the dividend-to-asset ratio. Year fixed effects (λ_t) account for macroeconomic shocks, industry fixed effects (θ_s) control for sectoral heterogeneity, state fixed effects (δ_j) capture regional variation, and firm fixed effects (μ_i) absorb time-invariant unobservable heterogeneity at the firm level. Standard errors are clustered at the firm level.

Figure 7 plots the dynamic treatment effects of the TensorFlow shock on the logarithm of intangible capital. Each coefficient represents the interaction between the firm's pre-

treatment share of AI workers and an event-time indicator relative to the year prior to the TensorFlow release ($t = -1$). The pattern shows no evidence of differential trends in intangible capital across firms with varying AI intensity before the shock, lending support to the parallel trends assumption. Following 2015, the treatment effects become increasingly positive and statistically significant, suggesting that AI-intensive firms experienced a persistent and growing accumulation of intangible capital in the years after TensorFlow's release. This dynamic pattern reinforces the causal interpretation that improvements in AI effectiveness stimulated investment in intangible assets, particularly among firms well-positioned to benefit from the technology.

Figure 7: Dynamic DiD Estimates: AI Workers and Intangible Capital

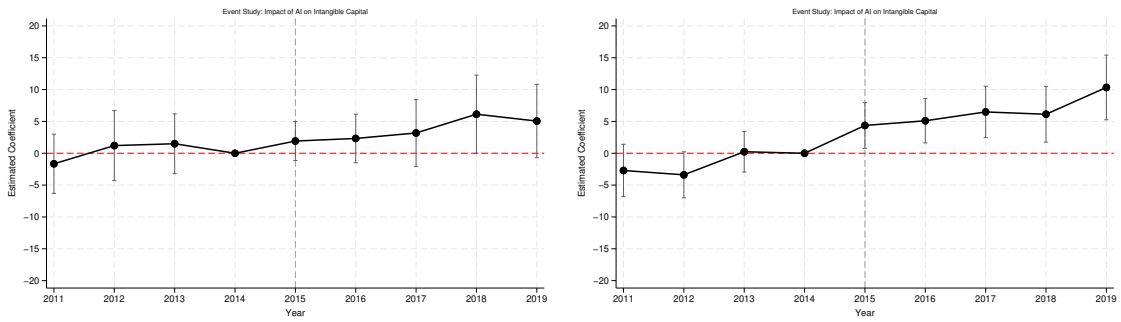


Note: This figure plots the estimated coefficients from a dynamic DiD regression of the impact of the TensorFlow shock on the logarithm of intangible capital. The coefficients represent the interaction between the firm's pre-2014 share of AI workers and year indicators, with 2014 as the omitted baseline year. Control variables include the one-year lag of the firm-level logarithm of total assets, logarithm of R&D expenditures, logarithm of capital expenditures, the cash-to-asset ratio, markup, and the dividend-to-asset ratio. The specification includes year, industry, state, and firm fixed effects. Standard errors are clustered at the firm level. Confidence intervals are shown at the 95% level.

Figure 8 examines the heterogeneity in the dynamic effects by firm size. Figure 8a displays the estimated coefficients for smaller firms, while Figure 8b presents the results for larger firms. Smaller (larger) firms are defined as those below (above) the median

of firm total assets within each industry and year. The treatment effect is muted and statistically indistinguishable from zero among smaller firms, suggesting that improvements in AI effectiveness had limited influence on their intangible capital accumulation. In contrast, larger firms exhibit strong and sustained increases in intangible capital post-shock, with the effect becoming economically meaningful by 2015 and persisting through the end of the sample period. This divergence highlights the scale-dependent nature of the AI–intangible capital complementarity and emphasizes the importance of firm size in shaping the responsiveness to technological shocks.

Figure 8: Dynamic DiD Estimates by Firm Size: AI Workers and Intangible Capital



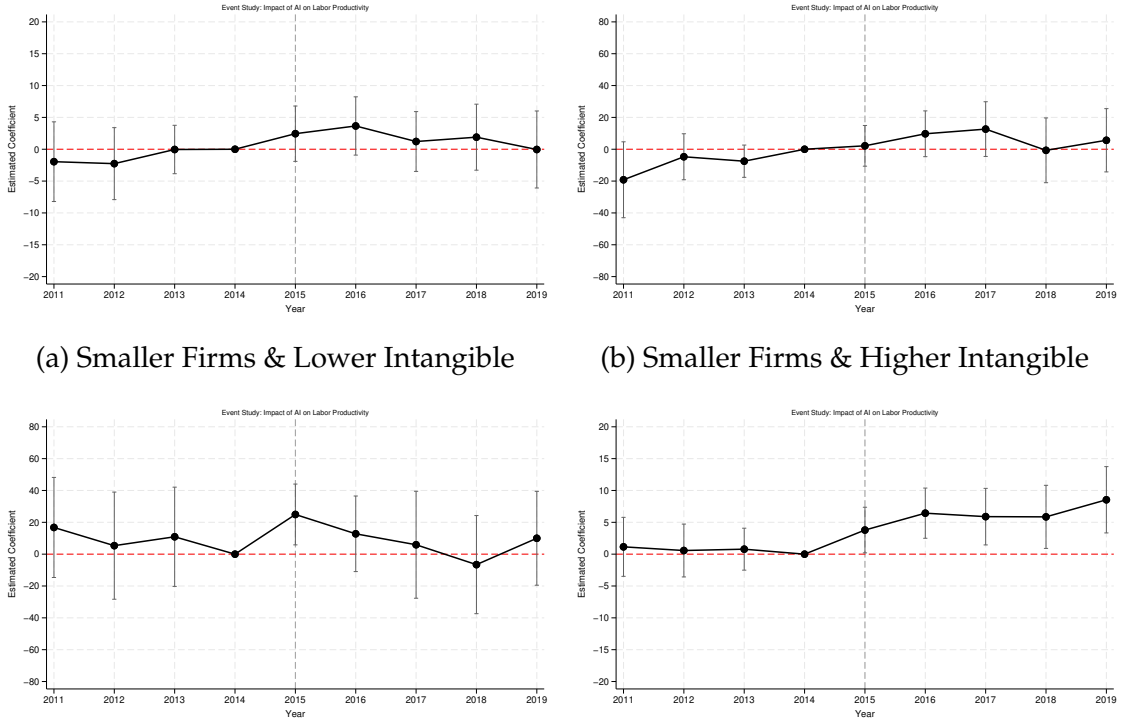
(a) Smaller Firms (b) Larger Firms

Note: This figure plots the estimated coefficients from a dynamic DiD regression of the impact of the TensorFlow shock on the logarithm of intangible capital, separately for smaller and larger firms. The coefficients represent the interaction between the firm's pre-2014 share of AI workers and year indicators, with 2014 as the omitted baseline year. Firm size is defined based on the median of total assets within each industry and year. Control variables include the one-year lag of the firm-level logarithm of total assets, logarithm of R&D expenditures, logarithm of capital expenditures, the cash-to-asset ratio, markup, and the dividend-to-asset ratio. The specification includes year, industry, state, and firm fixed effects. Standard errors are clustered at the firm level. Confidence intervals are shown at the 95% level.

Figure 9 further explores how the TensorFlow shock influenced labor productivity, conditional on both firm size and intangible capital intensity. Figures 9a and 9b display estimates for smaller firms with below- and above-median intangible capital, respectively, while Figures 9c and 9d present analogous results for larger firms. The clearest treatment effects appear in Panel (d): larger firms with high intangible capital show a sharp and persistent increase in labor productivity following the TensorFlow release. In contrast,

smaller firms with low or even high intangible capital exhibit flat or volatile trends, with no clear post-treatment gains. This four-way heterogeneity analysis strengthens our interpretation that the productivity-enhancing effects of AI are most pronounced when firms possess both scale and pre-existing intangible capacity.

Figure 9: Dynamic DiD Estimates: Labor Productivity, AI Workers, and Intangible Capital



(a) Smaller Firms & Lower Intangible

(b) Smaller Firms & Higher Intangible

(c) Larger Firms & Lower Intangible

(d) Larger Firms & Higher Intangible

Note: This figure plots the estimated coefficients from a dynamic DiD regression of the impact of the TensorFlow shock on the logarithm of labor productivity, separately for firms above and below the median of firm size and the median of intangible capital. The coefficients represent the interaction between the pre-2014 share of AI workers and year indicators, with 2014 as the omitted baseline year. Firm size and intangible capital are defined based on the median values of total assets and intangible capital ratio, respectively, within each industry and year. Control variables include the one-year lag of the firm-level logarithm of total assets, logarithm of R&D expenditures, logarithm of capital expenditures, the cash-to-asset ratio, markup, and the dividend-to-asset ratio. The specification includes year, industry, state, and firm fixed effects. Standard errors are clustered at the firm level. Confidence intervals are shown at the 95% level.

In light of the results in this section, we show that firms with higher pre-existing shares of AI workers experience greater productivity gains following the 2015 TensorFlow shock, with effects that are significantly stronger among larger firms with more intangible capi-

tal. These findings indicate that the productivity benefits of improved AI effectiveness are not uniform across firms but are instead amplified by both scale and intangible intensity.

5 Robustness Checks

To further assess the robustness of our causal findings, we conduct a series of complementary exercises. First, we complement our firm-level analysis with an industry-level robustness exercise using data from the Integrated Industry-Level Production Account (KLEMS), which allows us to assess whether the documented productivity and intangible capital responses generalize to a more aggregate and economy-wide setting that is less susceptible to firm-level measurement error and sample selection concerns. Second, we implement a placebo test to rule out spurious pre-trends and pre-existing differential dynamics across firms. Third, we re-estimate our empirical specifications using propensity score matching to address potential selection on observables. Fourth, we augment the benchmark specification with state- and industry-level linear time trends to control for differential regional and sectoral trends. Next, we explicitly control for firms' exposure to other digital technologies to ensure that our estimates are not driven by broader digital transformation. Moreover, we examine the sensitivity of our results to the definition of AI skills by replacing the broad AI skill measure with a narrower, more specialized classification of AI talent. Finally, we assess the robustness of our findings by disaggregating intangible capital into its main components such as knowledge capital, organizational capital, and off-balance-sheet intangibles, and by examining R&D expenditures as an alternative innovation input.

5.1 Industry-level Measures

A natural concern with our baseline firm-level analysis is that key variables such as labor productivity and intangible capital are constructed from Compustat balance sheet data and may therefore be subject to measurement error. In addition, because Compustat primarily covers large, publicly listed firms, one may question whether the documented effects are representative of the broader economy. To address these concerns, we complement our firm-level analysis with an industry-level exercise using data from the Integrated Industry-Level Production Account (KLEMS)[2], a widely used dataset that provides harmonized measures of production, inputs, and productivity at the industry level. These measures are based on national accounts and industry-level aggregation rather than firm financial statements, making them less susceptible to firm-specific reporting practices. As such, the KLEMS database provides a natural external validation of the mechanisms identified in our firm-level analysis.

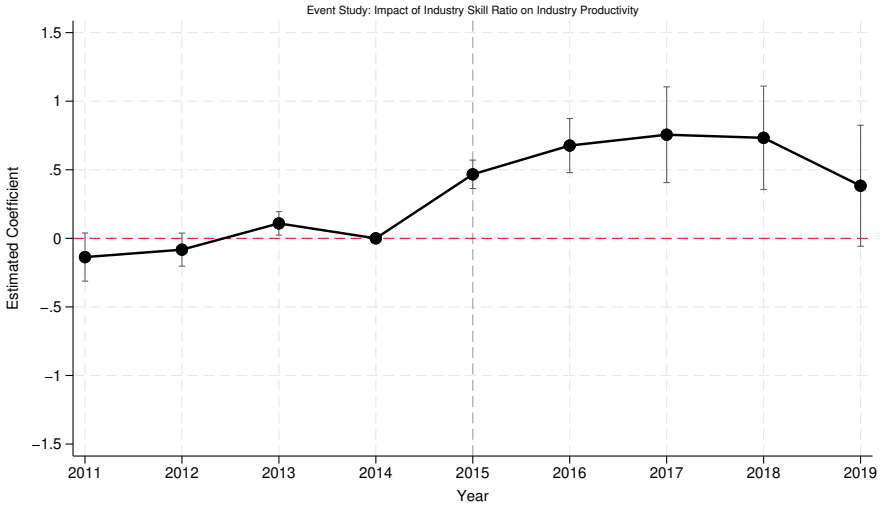
A data limitation is that direct measures of AI-skilled labor are not available at the industry level. To capture industry-level skill intensity in this setting, we therefore rely on the share of college-educated (skilled) workers in total industry employment, as reported in the KLEMS database. This measure is standard in the growth-accounting and skill-biased technological change literature and captures broad differences in human capital intensity across industries. Importantly, as documented in Figure 4a, the strong association between industry-level skill ratios and firm-level AI worker shares suggests that this variable provides a conceptually consistent proxy for skilled labor at the industry level.

We construct industry-level intangible capital by averaging the quantity indices of artistic originals, IT capital, R&D capital, and software capital reported in KLEMS. Since each component is indexed to 2017 = 100, we divide their sum by four to obtain a composite intangible capital index. Industry-level intangible intensity is defined as the ratio of intangible capital to the sum of intangible and physical capital.

[2]More information can be found here.

We replicate our baseline dynamic DiD specification using the 2014 industry-level skill ratio as the running variable. Figure 10 presents dynamic difference-in-differences estimates of the impact of the TensorFlow shock on industry-level labor productivity. The event-study coefficients show no evidence of differential pre-trends prior to 2015, while industries with higher pre-2014 skill shares experience a statistically significant increase in measured productivity following the shock. This pattern is consistent with our firm-level results and suggests that improvements in AI effectiveness translate into higher productivity through broader skill intensity at the industry level.

Figure 10: Dynamic DiD Estimates: Industry Skill Ratio and Productivity



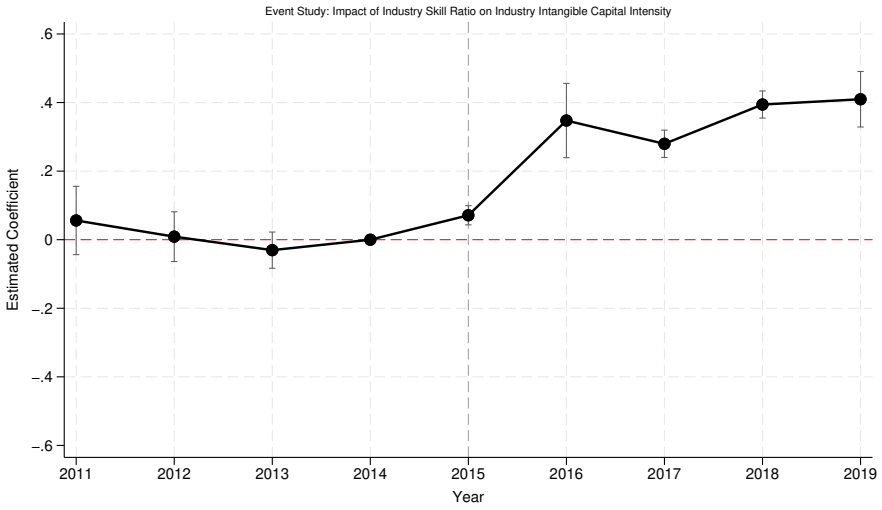
Note: This figure plots the estimated coefficients from a dynamic DiD regression of the impact of the TensorFlow shock on the industry-level productivity. The coefficients represent the interaction between the firm's pre-2014 share of AI workers and year indicators, with 2014 as the omitted baseline year. Control variables include the industry-level logarithm of gross output, skilled labor, unskilled labor, and intangible capital intensity. The specification includes year, and industry fixed effects. Standard errors are clustered at the year level. Confidence intervals are shown at the 95% level.

Figure 11 reports the corresponding dynamic estimates for industry-level intangible capital intensity. The results reveal a clear post-2015 increase in intangible intensity among skill-intensive industries. This finding mirrors our firm-level evidence and indicates that technological improvements associated with AI disproportionately stimulate intangible investment in industries with higher skill intensity.

Taken together, the industry-level evidence based on the KLEMS database strength-

ens the interpretation of our main results in two ways. First, it alleviates concerns that measurement error in firm-level Compustat data drives our findings. Second, it shows that the complementarity between skilled labor and intangible capital operates at a more aggregate level that is representative of the overall economy.

Figure 11: Dynamic DiD Estimates: Industry Skill Ratio and Intangible Capital Intensity



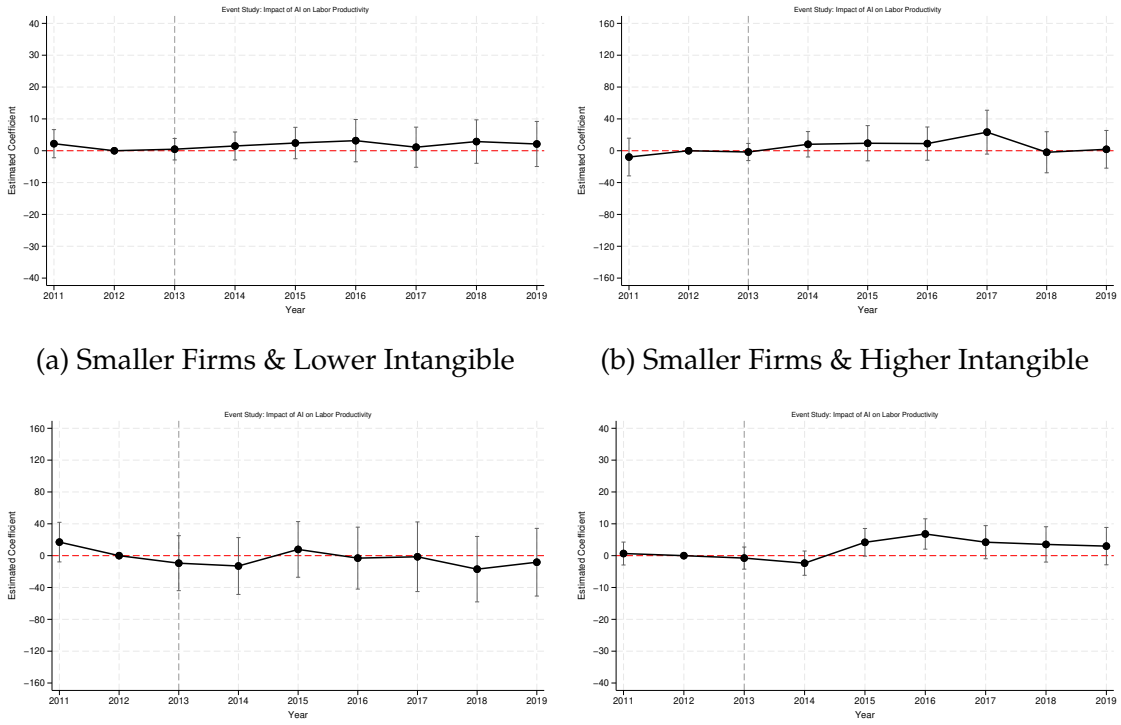
Note: This figure plots the estimated coefficients from a dynamic DiD regression of the impact of the TensorFlow shock on the industry-level intangible capital intensity. The coefficients represent the interaction between the firm's pre-2014 share of AI workers and year indicators, with 2014 as the omitted baseline year. Control variables include the industry-level logarithm of gross output. The specification includes year, and industry fixed effects. Standard errors are clustered at the year level. Confidence intervals are shown at the 95% level.

5.2 Placebo Test

As a robustness check, we conduct a placebo test by redefining the policy intervention year as 2013, two years prior to the actual release of Google's TensorFlow, and setting 2012 as the baseline year. This allows us to test whether our main findings could be driven by pre-existing trends or spurious correlations. The results, presented in Figure 12, reveal no systematic positive effect of the complementarity between intangible capital and skilled labor on labor productivity during this placebo period. In particular, we do not observe consistent and significant post-treatment productivity gains for large and high-intangible firms, in contrast to the pronounced effects identified in the actual treatment period start-

ing in 2015. This absence of placebo effects strengthens the causal interpretation of our benchmark results and supports the validity of the identification strategy.

Figure 12: Dynamic DiD Estimates - Placebo Test



(a) Smaller Firms & Lower Intangible

(b) Smaller Firms & Higher Intangible

(c) Larger Firms & Lower Intangible

(d) Larger Firms & Higher Intangible

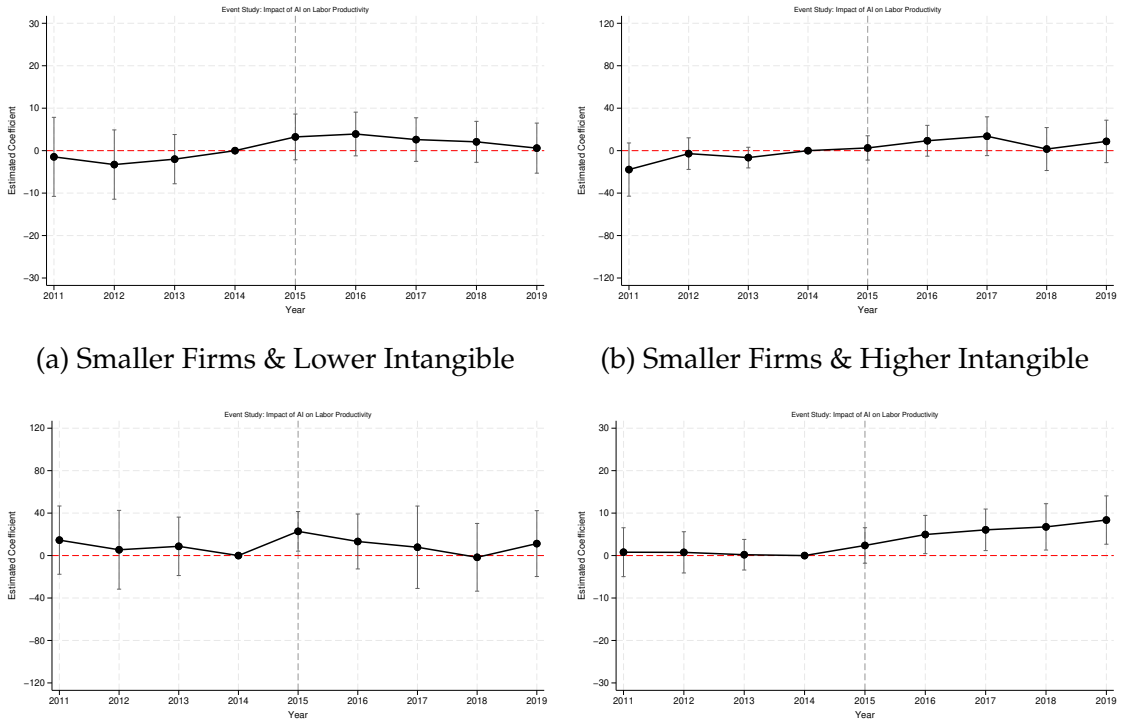
Note: This figure plots the estimated coefficients from a placebo dynamic DiD regression using 2013 as a fake policy year to test for spurious pre-trends in the relationship between AI intensity and productivity. The coefficients represent the interaction between the pre-2012 share of AI workers and year indicators, with 2012 as the omitted baseline year. The analysis is conducted separately for large and high-intangible firms, as defined by the median of total assets and intangible capital within industry and year. Control variables include the one-year lag of the firm-level logarithm of total assets, logarithm of R&D expenditures, logarithm of capital expenditures, the cash-to-asset ratio, markup, and the dividend-to-asset ratio. The specification includes year, industry, state, and firm fixed effects. Standard errors are clustered at the firm level. Confidence intervals are shown at the 95% level.

5.3 Propensity Score Matching

A potential concern with our baseline difference-in-differences design is that firms with higher pre-treatment AI intensity may differ systematically from other firms along observable dimensions that also predict productivity growth. To address this concern, we re-estimate our dynamic DiD specifications using a propensity score matching (PSM) ap-

proach.

Figure 13: Dynamic DiD Estimates - Propensity Score Matching



(a) Smaller Firms & Lower Intangible

(b) Smaller Firms & Higher Intangible

(c) Larger Firms & Lower Intangible

(d) Larger Firms & Higher Intangible

Note: This figure plots the estimated coefficients from a dynamic DiD regression of the impact of the TensorFlow shock on the logarithm of labor productivity, implementing a propensity score matching. The coefficients represent the interaction between the pre-2014 share of narrow AI-skilled workers and year indicators, with 2014 as the omitted baseline year. The analysis is conducted separately for firms above and below the median of firm size and the median of intangible capital, defined within each industry and year. Control variables include the one-year lag of the firm-level logarithm of total assets, logarithm of R&D expenditures, logarithm of capital expenditures, the cash-to-asset ratio, markup, and the dividend-to-asset ratio. The specification includes year, industry, state, and firm fixed effects. Standard errors are clustered at the firm level. Confidence intervals are shown at the 95% level.

Specifically, we match firms with above-median pre-2014 AI worker shares to observationally similar firms with lower AI exposure based on a rich set of pre-treatment characteristics, including firm size, intangible capital, R&D intensity, capital expenditures, cash holdings, and markups. Matching is conducted within industry and year to ensure comparability in technological and market environments. We then re-estimate our dynamic DiD specification on the matched sample.

Figure 13 presents the resulting dynamic DiD estimates. The key patterns closely

mirror our baseline results. Productivity gains following the TensorFlow shock remain concentrated among large, intangible-rich firms, while smaller firms or firms with lower intangible capital exhibit no systematic post-treatment effects. Importantly, we continue to observe flat and statistically insignificant coefficients in the pre-treatment period, reinforcing the parallel trends assumption.

Overall, these findings suggest that our baseline results are not driven by selection on observables or differences in pre-existing firm characteristics, but instead reflect a genuine complementarity between intangible capital and AI-skilled labor.

5.4 Controlling for Time Trends

A potential concern with our baseline difference-in-differences estimates is that firms with higher pre-period exposure to AI workers may be located in states or industries that follow systematically different technology or productivity trajectories over time. If such differential trends are correlated with AI adoption or intangible intensity, the estimated post-TensorFlow effects could partly reflect pre-existing state-level or industry-level dynamics rather than a causal response.

To address this concern, Table 4 augments the benchmark specification by explicitly allowing for linear time trends at the state and industry levels. Column (1) includes state-specific linear time trends, column (2) includes industry-specific linear time trends, and column (3) controls for both state- and industry-level trends simultaneously. Across all specifications, the estimated coefficients on the interaction between the post-TensorFlow indicator and the pre-treatment share of AI workers remain positive, statistically significant, and economically meaningful. Importantly, the triple interaction with lagged intangible capital is remarkably stable across columns, indicating that the complementarity between AI adoption and intangible capital in shaping productivity growth is not driven by differential state-level or industry-level secular trends.

Table 4: DiD Estimates: Controlling for Time Trends

	(1)	(2)	(3)
	Log Productivity	Log Productivity	Log Productivity
Post × Share of AI Workers$_{2014}$	4.302***	4.815***	5.051***
	(1.407)	(1.514)	(1.545)
Post × Share of AI Workers$_{2014}$ × L.Intangible Capital	6.008***	6.500***	6.485***
	(1.838)	(1.838)	(1.850)
Control Variables	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes
State FE	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes
State Time Trend	Yes	No	Yes
Industry Time Trend	No	Yes	Yes
Adjusted R^2	0.954	0.955	0.955
Observation	27711	27711	27711

Note: This table reports difference-in-differences regression estimates of the interaction between the post-TensorFlow indicator and the firm-level share of AI workers in 2014 on the logarithm of labor productivity, including the state-level and industry-level linear time trends. All specifications include the triple interaction with the lagged intangible capital. Control variables include the one-year lag of firm-level logarithm of total assets, logarithm of R&D expenditures, logarithm of capital expenditures, the cash-to-asset ratio, markup, and the dividend-to-asset ratio. Standard errors (in parentheses) are clustered at the firm level. * $p < .10$, ** $p < .05$, *** $p < .01$.

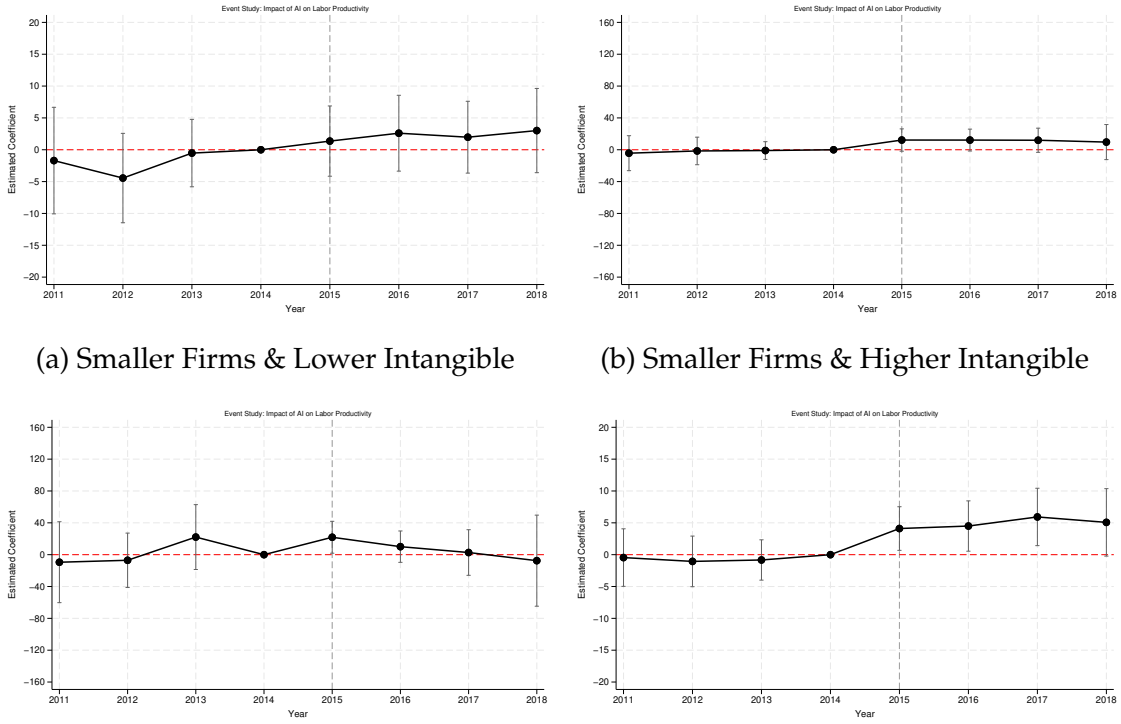
5.5 Controlling for Other Firm-level Technologies

Another potential concern is that our results may capture the effects of broader digital transformation or correlated technological investments rather than AI-specific mechanisms. In particular, firms that invest in AI-skilled labor may simultaneously adopt other digital technologies such as information technology infrastructure, data capabilities, or data analytics that independently influence productivity.

To address this concern, using the measures by Babina et al. (2024), we augment our baseline dynamic DiD specification by explicitly controlling for firm-level exposure to other technologies, including the shares of Information Technology (IT), data-related, and data analytics workers. These controls allow us to isolate the incremental contribution of AI-skilled labor over and above general digitalization trends. Due to data availability, this analysis is conducted over the 2011–2018 period.

Figure 14 reports the corresponding dynamic DiD estimates. The results remain qualitatively unchanged. Even after conditioning on other technology adoption, we continue to find a positive and statistically significant post-treatment productivity response among large firms with high intangible capital, while effects for other firm groups remain muted. Pre-treatment coefficients remain close to zero and statistically insignificant, providing further support for the validity of the identification strategy.

Figure 14: Dynamic DiD Estimates - Controlling for Other Firm-level Technologies



(a) Smaller Firms & Lower Intangible

(b) Smaller Firms & Higher Intangible

(c) Larger Firms & Lower Intangible

(d) Larger Firms & Higher Intangible

Note: This figure plots the estimated coefficients from a dynamic DiD regression of the impact of the TensorFlow shock on the logarithm of labor productivity, controlling other firm-level technologies such as share of Information Technology (IT), share of data, and share of data analytics through using the measures Babina et al. (2024). Since these additional controls are available until 2018 in the data, our final period in these DiDs is 2018. The coefficients represent the interaction between the pre-2014 share of narrow AI-skilled workers and year indicators, with 2014 as the omitted baseline year. The analysis is conducted separately for firms above and below the median of firm size and the median of intangible capital, defined within each industry and year. Control variables include the one-year lag of the firm-level logarithm of total assets, logarithm of R&D expenditures, logarithm of capital expenditures, the cash-to-asset ratio, markup, and the dividend-to-asset ratio. The specification includes year, industry, state, and firm fixed effects. Standard errors are clustered at the firm level. Confidence intervals are shown at the 95% level.

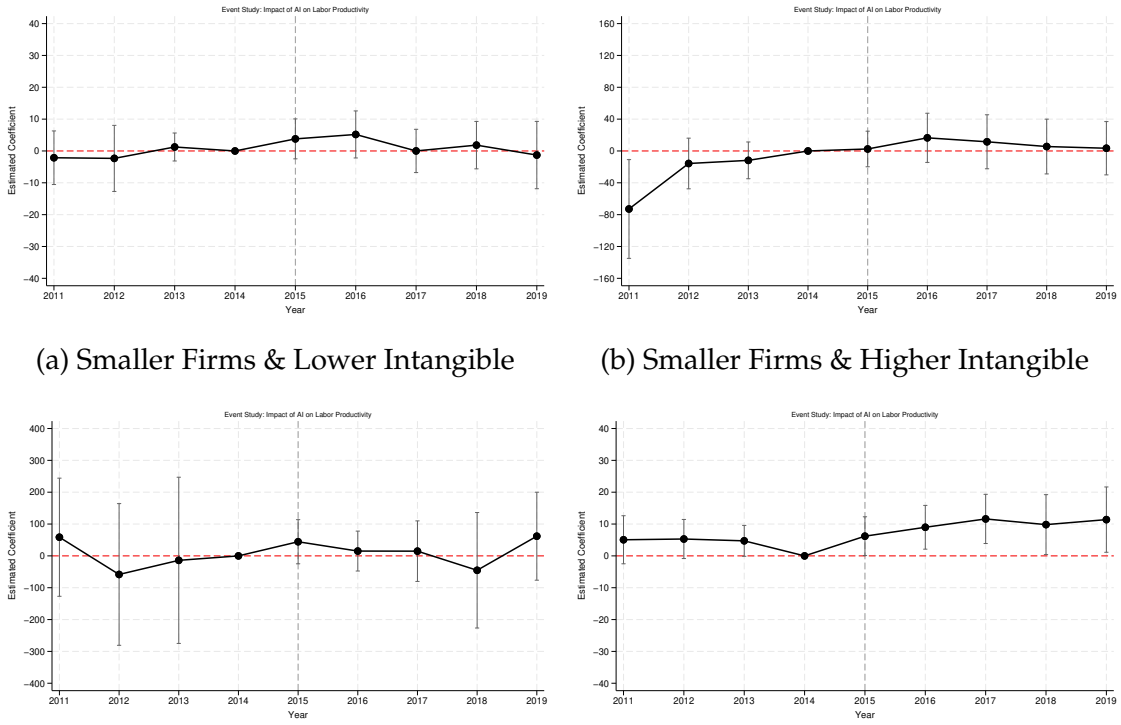
These findings indicate that our results are not driven by generic digital adoption or

concurrent technological trends, but instead reflect an AI-specific mechanism that operates through the interaction between AI-skilled labor, intangible capital, and firm scale.

5.6 Alternative AI Measure

In a separate robustness exercise, we examine whether the observed complementarity effects hold when using a more stringent definition of AI talent using the measures by Babina et al. (2024).

Figure 15: Dynamic DiD Estimates - Alternative AI Measure



(a) Smaller Firms & Lower Intangible

(b) Smaller Firms & Higher Intangible

(c) Larger Firms & Lower Intangible

(d) Larger Firms & Higher Intangible

Note: This figure plots the estimated coefficients from a dynamic DiD regression of the impact of the TensorFlow shock on the logarithm of labor productivity, incorporating an alternative measure of AI intensity based on narrow AI skills using the measures by Babina et al. (2024). The analysis is conducted separately for firms above and below the median of firm size and the median of intangible capital, defined within each industry and year. Control variables include the one-year lag of the firm-level logarithm of total assets, logarithm of R&D expenditures, logarithm of capital expenditures, the cash-to-asset ratio, markup, and the dividend-to-asset ratio. The specification includes year, industry, state, and firm fixed effects. Standard errors are clustered at the firm level. Confidence intervals are shown at the 95% level.

Figure 15 replicates our main analysis using the share of workers with narrow AI skills, highly specialized and directly AI-relevant competencies, rather than the broader skill classification used in the baseline. The results remain consistent such that we find a positive and significant productivity effect of the complementarity between intangible capital and AI-skilled labor, but only among firms that are both large and intangible-rich. This reinforces our main findings and suggests that the synergy mechanism is robust to the definition of AI skills, further highlighting that productivity gains are concentrated in firms with both the technological capacity and scale necessary to leverage AI talent effectively.

5.7 Intangible Capital Components

To further assess the robustness and interpretation of our baseline results, using the measures by Peters and Taylor (2017), we disaggregate intangible capital into its main components such as knowledge capital, organizational capital, and off-balance-sheet intangibles and additionally examine R&D expenditures as a conventional innovation input. Knowledge capital captures investments in the creation of new ideas and codified knowledge, while organizational capital reflects firm-specific managerial practices, coordination routines, and decision-making structures that govern the deployment of such knowledge. Off-balance-sheet intangibles account for intangible investments that are expensed rather than capitalized under accounting standards, including software development, data-related expenditures, process improvements, and organizational upgrading that do not appear on firms' balance sheets.

Table 5 shows that firms with higher pre-2014 AI worker shares experience significantly larger post-TensorFlow increases across all these components, with particularly strong effects for knowledge and organizational capital. We also document a significant rise in R&D expenditures, indicating that AI exposure is associated not only with broader

intangible accumulation but also with conventional innovation activity. Taken together, the consistency of these patterns across disaggregated intangible components and R&D expenditures confirms that our baseline intangible capital measure captures meaningful underlying investments in knowledge creation and organizational capacity rather than mechanical accounting effects.

Table 5: DiD Estimates: AI Workers and Intangible Capital Components

	(1)	(2)	(3)	(4)
	Knowledge Capital	Organizational Capital	Off-Balance-Sheet Intangibles	R&D
Post $\times$ Share of AI Workers$_{2014}$	13.11***	9.809***	8.480***	10.61***
	(1.794)	(1.895)	(1.530)	(1.670)
Control Variables	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes
State FE	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
Adjusted R^2	0.990	0.963	0.970	0.985
Observation	27712	27712	27712	27712

Note: This table reports difference-in-differences regression estimates of the interaction between the post-TensorFlow indicator and the firm-level share of AI workers in 2014. The dependent variables are alternative components of intangible capital such as the logarithms of knowledge capital, organizational capital, off-balance-sheet intangibles, and we also include the logarithm of R&D expenditures. The dependent variables are normalized by one-year lagged total assets. Control variables include the one-year lag of firm-level logarithm of total assets, logarithm of R&D expenditures, logarithm of capital expenditures, the cash-to-asset ratio, markup, and the dividend-to-asset ratio. Standard errors (in parentheses) are clustered at the firm level. * $p < .10$, ** $p < .05$, *** $p < .01$.

6 Conclusion

This paper studies how the interaction between intangible capital and skilled labor shapes firm-level productivity dynamics. To establish a causal link, we use firm-level data on AI-skilled workers as a proxy for skilled labor and exploit the 2015 release of Google's TensorFlow as a plausibly exogenous shock to AI effectiveness. Using a difference-in-differences framework, we show that productivity gains following this shock are concentrated among large, intangible-rich firms with higher pre-existing shares of AI-skilled labor. Dynamic DiD analyses reveal no evidence of differential pre-trends, and a compre-

hensive set of robustness checks confirms that our findings are not driven by selection, alternative definitions of AI skills, or broader digital transformation.

Our findings carry several implications for innovation and technology policy. First, policies aimed at promoting AI adoption are unlikely to generate uniform productivity gains unless they are accompanied by investments in complementary intangible assets, such as data infrastructure, software, and organizational capabilities. Improvements in AI effectiveness alone are insufficient; firms must possess the intangible capital necessary to integrate and scale these technologies within their production processes. Second, because the productivity benefits of AI are strongly increasing in firm size and intangible capital, broad-based AI support policies may inadvertently amplify productivity dispersion by disproportionately benefiting large and intangible-rich firms. This highlights a potential trade-off between fostering frontier innovation and mitigating widening gaps across firms. From a policy perspective, this suggests a role for targeted interventions that lower the fixed costs of intangible investment, particularly for smaller and intangible-poor firms, such as support for data access, managerial training, and organizational upgrading. Finally, our results highlight the importance of workforce policies that expand advanced digital and AI-related skills. By strengthening the supply of skilled labor, such policies can raise the returns to intangible investment and enhance firms' ability to translate technological advances into sustained productivity growth. Taken together, our findings emphasize that effective AI policy should be viewed not as a stand-alone technology intervention, but as part of a broader innovation ecosystem that jointly shapes skills, organizational capital, and firm dynamics.

Our analysis also highlights an important avenue for future research. Our reliance on Compustat data confines the analysis to publicly traded firms. Extending the framework to private firms including startups and small businesses through micro-level census or administrative data would offer a more comprehensive view of how intangible capital and skilled labor interact across the firm-size distribution.

References

Abowd, J. M., B. E. Stephens, L. Vilhuber, F. Andersson, K. L. McKinney, M. Roemer, and S. Woodcock (2009). 5. the lehd infrastructure files and the creation of the quarterly workforce indicators. In *Producer Dynamics*, pp. 149–234. University of Chicago Press.

Acemoglu, D. (1998). Why do new technologies complement skills? directed technical change and wage inequality. *The Quarterly Journal of Economics 113*(4), 1055–1089.

Acemoglu, D. (2002a). Directed technical change. *The Review of Economic Studies 69*(4), 781–809.

Acemoglu, D. (2002b). Technical change, inequality, and the labor market. *Journal of Economic Literature 40*(1), 7–72.

Adler, D. and L. B. Siegel (2019). *The productivity puzzle: Restoring economic dynamism*. CFA Institute Research Foundation.

Aghion, P., P. Howitt, and G. L. Violante (2002). General purpose technology and wage inequality. *Journal of Economic Growth 7*(4), 315–345.

Akcigit, U. and S. T. Ates (2023). What happened to us business dynamism? *Journal of Political Economy 131*(8), 2059–2124.

Altomonte, C., D. Favoino, M. Morlacco, T. Sonno, et al. (2021). Markups, intangible capital and heterogeneous financial frictions. Technical report, Centre for Economic Performance, LSE.

Andrews, D., C. Criscuolo, and P. N. Gal (2016). The best versus the rest: the global productivity slowdown, divergence across firms and the role of public policy.

Arrighetti, A., F. Landini, and A. Lasagni (2014). Intangible assets and firm heterogeneity: Evidence from Italy. *Research Policy 43*(1), 202–213.

Autor, D., D. Dorn, L. F. Katz, C. Patterson, and J. Van Reenen (2020). The fall of the labor share and the rise of superstar firms. *The Quarterly Journal of Economics 135*(2), 645–709.

Autor, D. H., L. F. Katz, and M. S. Kearney (2008). Trends in us wage inequality: Revising the revisionists. *The Review of Economics and Statistics 90*(2), 300–323.

Autor, D. H., F. Levy, and R. J. Murnane (2003). The skill content of recent technological change: An empirical exploration. *The Quarterly Journal of Economics 118*(4), 1279–1333.

Ayyagari, M., A. Demirguc-Kunt, and V. Maksimovic (2019). *The rise of star firms: intangible capital and competition*. The World Bank.

Babina, T., A. Fedyk, A. He, and J. Hodson (2024). Artificial intelligence, firm growth, and product innovation. *Journal of Financial Economics 151*, 103745.

Bartelsman, E. J. and Z. Wolf (2017). Measuring productivity dispersion.

Bessen, J. (2017). Information technology and industry concentration.

Bresnahan, T. F., E. Brynjolfsson, and L. M. Hitt (2002). Information technology, workplace organization, and the demand for skilled labor: Firm-level evidence. *The Quarterly Journal of Economics 117*(1), 339–376.

Brynjolfsson, E., D. Rock, and C. Syverson (2018). Artificial intelligence and the modern productivity paradox: A clash of expectations and statistics. In *The Economics of Artificial Intelligence: An Agenda*, pp. 23–57. University of Chicago Press.

Chen, S.-S., Y.-S. Chen, and S.-C. Peng (2025, August). The double-edged role of Artificial Intelligence in corporate decarbonization. Working paper, SSRN. Available at SSRN: https://ssrn.com/abstract=5362708.

Chen, W. X., T. T. Shi, and S. Srinivasan (2024, May). The value of AI innovations. Working Paper 24-069, Harvard Business School.

Chiavari, A. and S. S. Goraya (2025). The rise of intangible capital and the macroeconomic implications.

Comin, D. and T. Philippon (2005). The rise in firm-level volatility: Causes and consequences. *NBER Macroeconomics Annual 20*, 167–201.

Corrado, C., J. Haskel, and C. Jona-Lasinio (2017). Knowledge spillovers, ict and productivity growth. *Oxford Bulletin of Economics and Statistics 79*(4), 592–618.

Corrado, C., J. Haskel, C. Jona-Lasinio, and M. Iommi (2016). Intangible investment in the eu and us before and since the great recession and its contribution to productivity growth. Technical report, EIB Working Papers.

Corrado, C., C. Hulten, and D. Sichel (2009). Intangible capital and us economic growth. *Review of Income and Wealth 55*(3), 661–685.

Corrado, C. A. and C. R. Hulten (2010). How do you measure a" technological revolution"? *American Economic Review 100*(2), 99–104.

Crouzet, N. and J. Eberly (2023). Rents and intangible capital: A q+ framework. *The Journal of Finance 78*(4), 1873–1916.

Crouzet, N., J. Eberly, A. Eisfeldt, and D. Papanikolaou (2022a). Intangible capital, nonrivalry, and growth. *Available at SSRN*.

Crouzet, N. and J. C. Eberly (2019). Understanding weak capital investment: The role of market concentration and intangibles. Technical report, National Bureau of Economic Research.

Crouzet, N., J. C. Eberly, A. L. Eisfeldt, and D. Papanikolaou (2022b). The economics of intangible capital. *Journal of Economic Perspectives 36*(3), 29–52.

De Loecker, J., J. Eeckhout, and G. Unger (2020). The rise of market power and the macroeconomic implications. *The Quarterly Journal of Economics 135*(2), 561–644.

De Ridder, M. (2024). Market power and innovation in the intangible economy. *American Economic Review 114*(1), 199–251.

Decker, R. A., J. C. Haltiwanger, R. S. Jarmin, and J. Miranda (2018). Changing business dynamism and productivity: Shocks vs. Technical report, Responsiveness. Working Paper 24236. National Bureau of Economic Research.

Eisfeldt, A. L. and D. Papanikolaou (2014). The value and ownership of intangible capital. *American Economic Review 104*(5), 189–94.

Engberg, E., M. Koch, M. Lodefalk, and S. Schroeder (2025). Artificial intelligence, tasks, skills, and wages: Worker-level evidence from Germany. *Research Policy 54*(8), 105285.

Ewens, M., R. H. Peters, and S. Wang (2019). *Acquisition prices and the measurement of intangible capital*. National Bureau of Economic Research.

Goldin, C. and L. F. Katz (1998). The origins of technology-skill complementarity. *The Quarterly Journal of Economics 113*(3), 693–732.

Greenwood, J., Z. Hercowitz, and P. Krusell (1997). Long-run implications of investment-specific technological change. *The American Economic Review*, 342–362.

Greenwood, J. and M. Yorukoglu (1997). 1974. In *Carnegie-Rochester conference series on public policy*, Volume 46, pp. 49–95. Elsevier.

Griliches, Z. (1969). Capital-skill complementarity. *The Review of Economics and Statistics*, 465–468.

Gutiérrez, G. and T. Philippon (2016). Investment-less growth: An empirical investigation. Technical report, National Bureau of Economic Research.

Gutiérrez, G. and T. Philippon (2017). Declining competition and investment in the us. Technical report, National Bureau of Economic Research.

Haskel, J. and S. Westlake (2017). *Capitalism without capital*. Princeton University Press.

Hornstein, A., P. Krusell, and G. L. Violante (2005). The effects of technical change on labor market inequalities. In *Handbook of Economic Growth*, Volume 1, pp. 1275–1370. Elsevier.

Katz, L. F. et al. (1999). Changes in the wage structure and earnings inequality. In *Handbook of Labor Economics*, Volume 3, pp. 1463–1555. Elsevier.

Katz, L. F. and K. M. Murphy (1992). Changes in relative wages, 1963–1987: supply and demand factors. *The Quarterly Journal of Economics 107*(1), 35–78.

Krusell, P., L. E. Ohanian, J.-V. Ríos-Rull, and G. L. Violante (2000). Capital-skill complementarity and inequality: A macroeconomic analysis. *Econometrica 68*(5), 1029–1053.

Ladika, T., R. Döttling, and E. C. Perotti (2025). Creating intangible capital. *Available at SSRN 3479152*.

Lev, B. and S. Radhakrishnan (2005). The valuation of organization capital. In *Measuring Capital in the New Economy*, pp. 73–110. University of Chicago Press.

McGrattan, E. R. (2020). Intangible capital and measured productivity. *Review of Economic Dynamics 37*, S147–S166.

McGrattan, E. R. and E. C. Prescott (2010). Unmeasured investment and the puzzling us boom in the 1990s. *American Economic Journal: Macroeconomics 2*(4), 88–123.

O'Mahony, M. and M. Vecchi (2009). R&D, knowledge spillovers and company productivity performance. *Research Policy 38*(1), 35–44.

Peters, R. H. and L. A. Taylor (2017). Intangible capital and the investment-q relation. *Journal of Financial Economics 123*(2), 251–272.

Piva, M., E. Santarelli, and M. Vivarelli (2005). The skill bias effect of technological and organisational change: Evidence and policy implications. *Research Policy 34*(2), 141–157.

Rammer, C., G. P. Fernández, and D. Czarnitzki (2022). Artificial intelligence and industrial innovation: Evidence from German firm-level data. *Research Policy 51*(7), 104555.

Rock, D. (2019). Engineering value: The returns to technological talent and investments in artificial intelligence. *Available at SSRN 3427412*.

Solow, R. M. (1957). Technical change and the aggregate production function. *The Review of Economics and Statistics*, 312–320.

Sun, Q. and M. Z. Xiaolan (2019). Financing intangible capital. *Journal of Financial Economics 133*(3), 564–588.

Van Ark, B., V. Chen, and K. Jäger (2013). European productivity growth since 2000 and future prospects. *International Productivity Monitor* (25), 65.

Violante, G. L. (2008). Skill-biased technical change. *The New Palgrave Dictionary of Economics 2*, 1–6.

Yang, C.-H. (2022). How artificial intelligence technology affects productivity and employment: Firm-level evidence from Taiwan. *Research Policy 51*(6), 104536.

Zhang, L. (2019). Intangible-investment-specific technical change, concentration and labor share.

Appendix

A Additional Tables

Table A.1: Firm-Level Constructed Variables and Descriptions

Variable	Description	Data and Reference
Labor Productivity	$\frac{\text{Sales } (sale) \text{ (\$ million)}}{\text{Employee } (emp) \text{ (thousands)}}$	Compustat
Intangible Capital Ratio	$\frac{\text{Intangible Capital (\$ million)}}{\text{Intangible Capital (\$ million)} + \text{Property, Plant and Equipment } (ppegt) \text{ (\$ million)}}$	Compustat, Peters and Taylor (2017)
Markup	$0.85 \frac{\text{Sales } (sale) \text{ (\$ million)}}{\text{Cost of Goods Sold } (cogs) \text{ (\$ million)}}$	Compustat, De Loecker et al. (2020)
Firm Age	Difference between current year and firm's founding year	Compustat, Jay R. Ritter's Website
Cash-to-Assets	Cash (ch) (\$ million) divided by assets (at) (\$ million)	Compustat
Dividends-to-Assets	Dividends to common shareholders (dvc) (\$ million) divided by lagged book assets (at) (\$ million)	Compustat

Note: This table summarizes the firm-level constructed variables and their brief descriptions in the Compustat sample.

Table A.2: Sample Selection: Firm-Year Panel

Step	Dropped Firms	Dropped Observations	Remaining Firms	Remaining Observations
Initial sample (2011–2019)			14,571	84,522
Exclude Financials, Utilities, and Other Industries	6,354	37,286	8,217	47,236
After dropping singletons and missing values in regressions	4,257	19,525	3,960	27,711
Final sample			**3,960**	**27,711**

Note: This table reports the sample selection for the 2011-2019 firm-year panel used in the analysis. Industry exclusions follow standard practice: financials (SIC 6000–6999), utilities (SIC 4000–4999), and other industries with SIC $\geq$ 9000.

Table A.3: Sample Composition by Year and Industry

Panel A: Sample Composition by Year		
Year	Number of Observations	Percentage of Observations
2011	2,810	10.1
2012	2,960	10.7
2013	3,199	11.5
2014	3,461	12.5
2015	3,401	12.3
2016	3,296	11.9
2017	3,071	11.1
2018	2,863	10.3
2019	2,650	9.6
Total	27711	100.0
Panel B: Sample Composition by Industry		
Industry	Number of Observations	Percentage of Observations
Consumer Non-Durables	1,484	5.4
Consumer Durables	880	3.2
Manufacturing	3,100	11.2
Oil, Gas, and Coal	1,894	6.8
Chemicals	997	3.6
High Tech	6,164	22.2
Telephone and Television	804	2.9
Wholesale and Retail	3,185	11.5
Healthcare	4,786	17.3
Other	4,417	15.9
Total	27711	100.0

Note: This table summarizes the sample distribution by year (Panel A) and by Fama–French 12-industry classification (Panel B).

Table A.4: Summary Statistics

	Mean	SD	P25	P50	P75	Min	Max	Count
Log Assets	5.4431	2.4689	3.6973	5.6356	7.2095	0	12.5495	27711
Log R&D	-3.7840	2.8017	-5.9557	-3.6378	-1.7157	-12.4934	5.0502	27711
Log Capital Expenditures	2.4772	2.0666	0.4906	2.2548	3.9287	-0.0066	9.9667	27711
Cash-to-Assets	0.1645	0.1905	0.0342	0.0980	0.2164	-0.8256	1	27659
Log Firm Age	3.1772	0.8137	2.7081	3.2581	3.7842	0.6931	5.1874	27711
Markup	2.0992	9.7264	1.0628	1.3217	1.9042	-22.6266	1115.2	27425
Dividends-to-Assets	0.0155	0.0926	0	0	0.0118	-0.0001	9.7985	27711
Log Labor Productivity	3.8965	1.7053	2.9871	4.2938	5.0159	-0.2807	10.1950	27711
Log Intangible Capital	4.7996	2.2689	3.1371	4.8632	6.3939	0	12.1650	27711
Share of AI Workers	0.0029	0.0054	0	0.0009	0.0036	0	0.1577	27711

Note: This table reports summary statistics for the main variables used in the analysis. P25, P50, and P75 denote the 25th percentile, median, and 75th percentile, respectively.

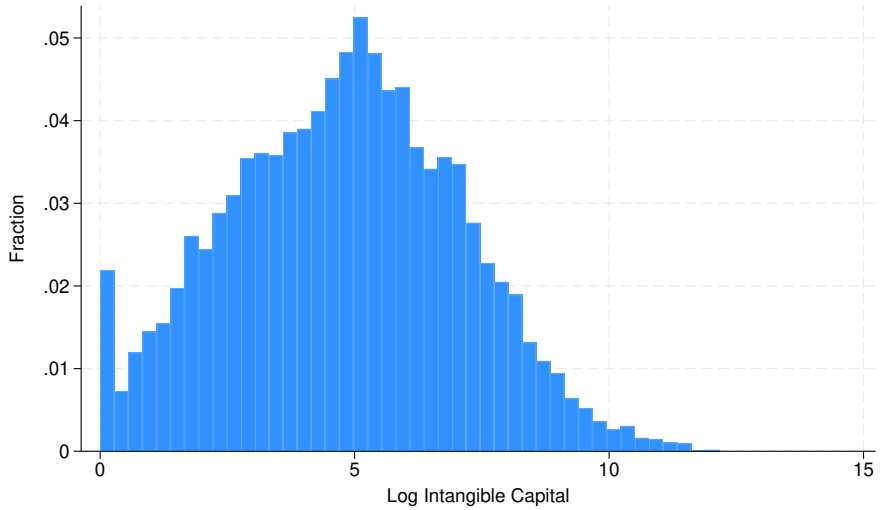
Table A.5: Pairwise Correlation Matrix

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
(1) Log Assets	1.00									
(2) Log R&D	-0.66*	1.00								
(3) Log Capital Expenditures	0.89*	-0.65*	1.00							
(4) Cash-to-Assets	-0.37*	0.49*	-0.38*	1.00						
(5) Firm Age	0.38*	-0.35*	0.33*	-0.21*	1.00					
(6) Markup	-0.02*	0.06*	-0.03*	0.06*	-0.03*	1.00				
(7) Dividends-to-Assets	0.05*	-0.06*	0.04*	0.00	0.01	-0.00	1.00			
(8) Log Labor Productivity	0.83*	-0.71*	0.71*	-0.41*	0.36*	-0.02*	0.06*	1.00		
(9) Log Intangible Capital	0.83*	-0.42*	0.68*	-0.21*	0.41*	0.00	0.02*	0.64*	1.00	
(10) Share of AI Workers	0.16*	0.11*	0.09*	0.09*	0.02*	0.03*	-0.01*	0.16*	0.24*	1.00

Note: This table reports pairwise correlations. Variables are winsorized at the 1st and 99th percentiles. An asterisk (*) indicates significance at the 10% level.

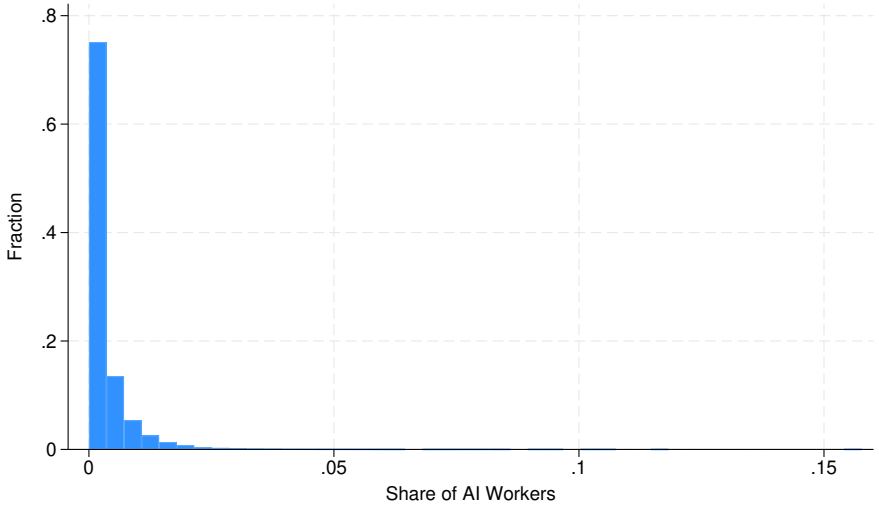
B Additional Figures

Figure B.1: Intangible Capital - Histogram



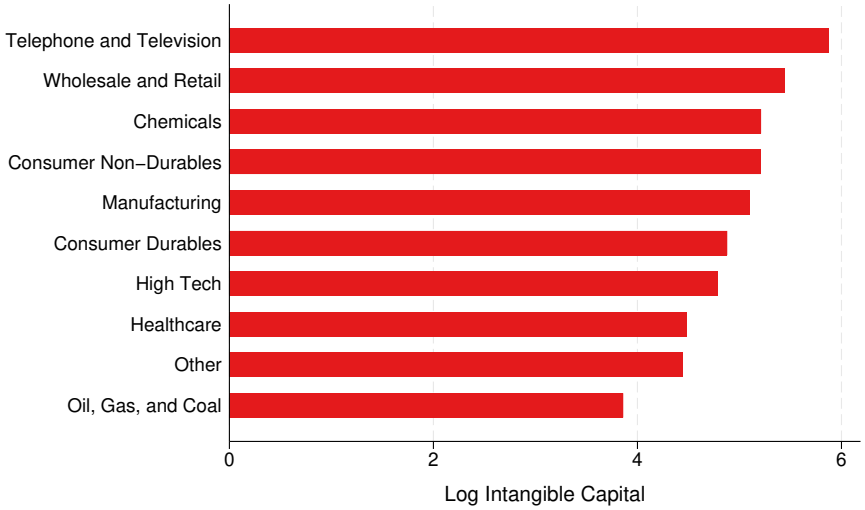
Note: This figure shows the histogram of intangible capital.

Figure B.2: Share of AI Workers - Histogram



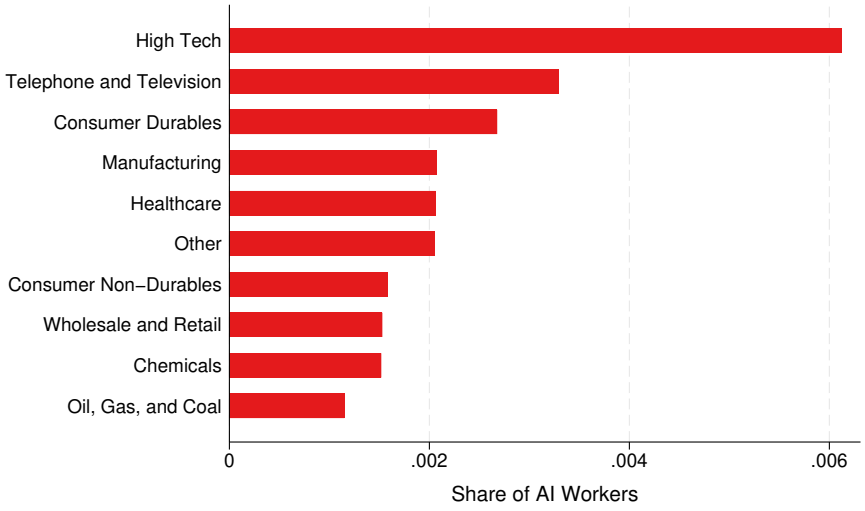
Note: This figure shows the histogram of the firm-level share of AI workers.

Figure B.3: Intangible Capital - Industry Variation



Note: This figure shows the average of intangible capital for Fama-French industries.

Figure B.4: Share of AI Workers - Industry Variation



Note: This figure shows the average of share of AI workers for Fama-French industries.