Conditional Gains: When AI Investment Enhances Firm Efficiency

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Abstract

The rapid adoption of artificial intelligence (AI) in the corporate world has raised important questions about its impact on firm performance. This paper examines whether investments in AI—measured by the share of AI-skilled workers—are associated with improvements in firm efficiency. The analysis reveals that AI investment alone does not lead to higher efficiency. That is, firms employing more AI-skilled labor do not, on average, perform more efficiently than others. However, the results show that this relationship depends on firm context. Firms operating in more competitive markets appear to benefit more from AI investment. Additionally, firms that engage more heavily in tax avoidance also realize greater efficiency gains from AI, possibly due to their more aggressive or strategic resource allocation practices.

JEL classifications: D40, E22, G30, H26, L11.

Keywords: artificial intelligence (AI), firm efficiency, market power, tax avoidance.

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1. Introduction

The integration of artificial intelligence (AI) has become critically important for modern corporations, offering the potential to transform decision-making, streamline operations, and drive innovation (Babina et al., 2024). Yet, a key question remains: in which specific areas can AI truly deliver value and enhance firm performance?

Firm efficiency is of paramount importance for a corporation, as it directly impacts profitability, competitiveness, and long-term sustainability. Efficient firms utilize their resources effectively, reduce unnecessary costs, and maximize output (Baik et al., 2013). High efficiency also improves the firm's outcomes, enabling it to respond swiftly to shifts in consumer preferences, technological advancements, and competitive pressures (Ebben & Johnson, 2005). Moreover, efficiency is closely linked to financial health, as efficient resource allocation can strengthen financial performance, improve returns to shareholders, and facilitate sustainable growth (Barney, 1991).

In this study, I find that AI investment, by itself, does not show a direct association with firm efficiency. This suggests that simply increasing the share of AI-skilled workers in a firm does not automatically translate into measurable productivity gains as complementary investments might be needed (see also Brynjolfsson & Hitt, 2000; Brynjolfsson, Rock, & Syverson, 2021). However, the analysis reveals two important conditions under which AI investment appears to be more beneficial. First, firms with lower market power tend to benefit more from AI adoption. A plausible explanation is that these firms operate in more competitive environments, where efficiency gains are essential for survival and growth (Syverson, 2011). Facing tighter margins and less pricing power, such firms may be more incentivized to use AI strategically to maintain or improve their competitive position (Bloom, Draca, & Van Reenen, 2016; Porter & Strategy, 1980). In contrast, firms with greater market power may lack the same urgency to exploit AI for efficiency, as their dominant position already allows for operational slack.

Second, I find that firms engaging in greater tax avoidance also benefit more from AI investment. This relationship suggests that such firms may possess a more aggressive or strategic managerial approach, characterized by a willingness to exploit available tools—financial or technological—to enhance performance (Dyreng, Hanlon, & Maydew, 2010). Tax avoidance requires a level of sophistication in resource planning and regulatory navigation, indicating that these firms may also be more adept at identifying and implementing AI solutions that improve internal processes (Hanlon & Heitzman, 2010). By reallocating resources more efficiently and investing in high-impact technologies, tax-avoiding firms might be better positioned to capture the productivity-enhancing potential of AI (Hasan, Lobo, & Qiu, 2021). Additionally, these firms may have a more risk-tolerant or innovative culture that encourages the exploration of advanced technologies like AI to maintain competitive advantage and operational agility (Baghdadi, Podolski, & Veeraraghavan, 2022). In this sense, tax avoidance could serve as a proxy for strategic intensity or management quality, helping to explain why the efficiency benefits of AI are more pronounced in this subset of firms (Koester, Shevlin, & Wangerin, 2017).

Why does not AI investment show a direct link to firm efficiency? Several factors can explain this outcome. AI investments often require substantial upfront costs and yield returns only after extended periods; thus, firms might not yet have experienced measurable efficiency gains within the study's period (Davenport, Guha, & Grewal, 2021). Additionally, AI resources could be directed toward strategic objectives unrelated directly to immediate operational efficiency (Cockburn, Henderson, Stern, et al., 2018). Firms also frequently face challenges integrating AI effectively into their existing frameworks (Forbes Expert Panel, 2023). In addition, inadequate training or poor strategic choices might further impede the realization of efficiency benefits (Davenport & Ronanki, 2018). Sectoral heterogeneity and firm-specific differences may also hide underlying relationships, as certain industries or individual firms could benefit significantly from AI while others may not (Heyman, Norbäck, & Persson, 2021). Lastly, it is possible that efficiency gains become evident only after surpassing a certain level of AI adoption (Brynjolfsson, Rock, & Syverson, 2019).

This paper offers several contributions to the existing literature. First, it enriches the broad body of research on firm efficiency by showing that AI investment, when considered in isolation, does not necessarily lead to improved efficiency outcomes. This challenges the prevailing assumption that the adoption of cutting-edge technologies such as AI automatically translates into performance gains, and instead suggests that complementary factors (such as organizational readiness and strategic alignment) may be critical in realizing AI's potential. Second, the findings offer a timely reflection on the current stage of the AI revolution in the corporate sector. The absence of a strong direct link between AI investment and efficiency indicates that the effects of AI may take longer to materialize. As such, this paper provides empirical support for the view that we are still in the early phases of technological diffusion, where firms are experimenting with AI capabilities but have not yet fully integrated them.

2. Methodology

2.1. Datasets and used sample selection

I rely on multiple data sources to address the research question. Firm-level accounting data are drawn from Compustat, while firm efficiency is measured using the Data Envelopment Analysis (DEA) approach proposed by Demerjian, Lev, and McVay (2012). AI investment is based on the share of AI-related workers in a firm, as constructed by Babina et al. (2024).[1] Measures of market power follow the methodology of De Loecker, Eeckhout, and Unger (2020). Firms operating in the financial and utilities sectors are omitted from the analysis (SIC codes 4900-4999 and 6000-6999). All continuous variables are winsorized at the 1% level to mitigate the influence of outliers.

2.2. Econometric model

To examine the association between AI investment and firm efficiency I use the following OLS model:

$$Efficiency_{i,t+1} = \beta_0 + \beta_1 AI_{i,t} + \boldsymbol{\beta}_2 \mathbf{Controls}_{i,t} + \phi_i + \chi_t + \varepsilon_{i,t}. \tag{1}$$

In the above specification, $Efficiency$ indicates the efficiency of a firm. AI denotes the share of AI workers in a firm, **Controls** is a vector of firm specific characteristics, while ϕ and χ represent firm- and year-fixed effects. Finally, ε is the error term. The dependent variable is measured one year ahead to allow sufficient time for AI-related investments to translate into observable improvements in firm efficiency.

3. Results

Summary statistics are reported in Table 1.[2] The average (median) firm efficiency is approximately 0.34 (0.29), suggesting that many firms operate with substantial inefficiencies. The share of AI investment remains relatively low, consistent with findings in Liu and Zhang (2025). This implies that throughout most of the sample period, only a limited number of firms employed a significant proportion of AI-related workers.

[Insert Table 1 about here]

Turning to the baseline analysis in Table 2, the results indicate no statistically significant relationship between AI investment and firm efficiency in isolation. Across all model specifications, the coefficient for the AI variable is insignificant. To account for potential lagged effects—where AI adoption may require time to manifest—I extended the analysis to include future efficiency measures up to five years ahead. As shown in Table OA3, these lagged specifications similarly reveal no significant association. To explore sectoral variation, I applied the baseline model to individual industries (Table OA4). With the exception of *Construction*, where AI investment correlates negatively with efficiency, no industry exhibits a statistically meaningful link between AI investment and efficiency outcomes.

1. Further details on the construction of the firm efficiency measure can be found in Online Appendix A, and the derivation of the AI investment measure is provided in Online Appendix B.

2. The definition of all variables is in Table OA1, while the Pearson correlations are found in Table OA2.

[Insert Table 2 about here]

I then examine whether the relationship between AI investment and firm efficiency varies across different competitive environments. As shown in Table 3, the interaction term between AI investment and markup is negative and statistically significant. This suggests that, for a given level of AI investment, firms operating with lower markups—indicative of more competitive markets—tend to exhibit higher efficiency. The findings are consistent with the notion that firms with substantial market power may become complacent and fail to leverage AI effectively, whereas firms operating in highly competitive environments—where survival depends on operational efficiency—are more likely to adopt and utilize AI in a productive manner.

[Insert Table 3 about here]

Finally, I examine the interaction between AI investment and various proxies for tax avoidance, with the results presented in Table 4. Across all specifications, the interaction terms between AI investment and the effective tax rate (ETR) measures are negative and statistically significant. It is important to note that lower values of these ETR proxies indicate greater tax avoidance. Therefore, the findings suggest that, for a given level of AI investment, firms that engage in more tax avoidance tend to achieve higher efficiency, while those with higher tax payments perform worse in terms of efficiency. This finding is consistent with the idea that firms engaging in tax avoidance may be more strategic in resource allocation, allowing them to implement AI more effectively. In contrast, firms with higher tax payments may lack the flexibility or incentive to fully capitalize on AI investments.

[Insert Table 4 about here]

Additionally, given that only a limited number of firms make substantial AI investments, I conduct a robustness check by narrowing the sample to include only those firms with strictly positive AI investment at the beginning of the sample period. Within this smaller subset, the interaction between AI investment and market power remains statistically significant—and, if anything, appears even stronger. In contrast, the interaction terms involving effective tax rate (ETR) proxies are not statistically significant. These results are reported in Table OA5.

To better show the impact of the interaction terms, the marginal effects are also displayed in the Figure 1 below.

[Insert Figure 1 about here]

4. Conclusion

Understanding how investment in artificial intelligence (AI) is associated with firm efficiency is vital for both corporate strategy and economic policy. This study investigates this relationship and finds no direct association between AI investment and firm efficiency. However, it shows that firms operating in more competitive environments and those engaging in greater tax avoidance tend to benefit more from AI. The lack of a strong overall effect may reflect the early stage of AI adoption during the sample period, when most firms report minimal AI-related investments. As AI becomes more widespread, future research using more updated data will be able to better assess [AI's] true impact on firm performance, thus guiding both managerial decisions and targeted policy interventions.

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Table 1: Summary Statistics

Variable	Obs.	Mean	Std. Dev.	Min	p25	p50	p75	Max
Efficiency	51,685	0.339	0.182	0.000	0.228	0.286	0.394	1.000
AI	51,685	0.000	0.001	0.000	0.000	0.000	0.000	0.010
Size	51,685	6.169	2.294	0.034	4.512	6.085	7.755	12.092
RD	51,685	1.688	2.006	0.000	0.000	0.697	3.172	6.225
CAPX	51,685	0.135	0.121	0.000	0.060	0.099	0.167	0.953
Leverage	51,685	0.232	0.310	0.000	0.024	0.181	0.336	4.382
INTAN	51,685	0.154	0.185	0.000	0.005	0.077	0.244	0.752
ROA	51,685	-0.044	0.457	-11.407	-0.026	0.038	0.080	0.427
MTB	51,685	3.065	6.426	-37.294	1.230	2.121	3.708	48.028
Age	51,685	2.687	0.834	0.693	2.079	2.708	3.332	4.220
Sales_growth	51,685	0.220	0.804	-1.000	-0.018	0.085	0.234	9.049
Markup	44,465	0.403	0.463	-2.506	0.105	0.281	0.585	2.986
CASHETR	33,029	0.274	0.202	0.002	0.135	0.254	0.356	1.000
CASHETR_3s	30,173	0.278	0.187	0.003	0.161	0.261	0.349	1.000
CASHETR_adj	33,029	-0.002	0.199	-0.382	-0.136	-0.026	0.076	0.828
CASHTAX_NC	44,782	0.005	0.038	-0.281	-0.009	-0.002	0.006	2.400

Notes: The definitions of all variables can be found in Appendix Table OA1.

Table 2: Baseline Results

	(1)	(2)
AI	0.014	-0.602
	[0.013]	[-0.579]
Size		0.030***
		[13.310]
RD		-0.007***
		[-3.026]
CAPX		-0.005
		[-0.562]
Leverage		0.023***
		[4.960]
INTAN		-0.154***
		[-15.163]
ROA		0.020***
		[6.858]
MTB		0.001***
		[6.487]
Age		-0.000
		[-0.084]
Sales_growth		0.004***
		[3.050]
Constant	0.340***	0.179***
	[1,016.773]	[10.919]
Observations	59,836	51,685
Adjusted R^2	0.633	0.654
Firm effects	Yes	Yes
Year effects	Yes	Yes

Notes: The dependent variable in all regressions is firm efficiency. T-statistics, shown in brackets, are robust and clustered at the firm level. Stars, ***, **, *, indicate statistical significance at the 1%, 5%, and 10%, respectively. The definitions of all variables can be found in Appendix Table OA1.

Table 3: Market Power Channel

	(1)	(2)
AI	3.015**	2.177
	[2.124]	[1.619]
Markup	0.110***	0.108***
	[23.053]	[21.296]
AI×Markup	-4.129***	-3.259**
	[-2.597]	[-2.099]
Size		0.026***
		[14.087]
RD		-0.009***
		[-4.568]
CAPX		-0.019**
		[-2.439]
Leverage		0.011***
		[2.861]
INTAN		-0.141***
		[-16.486]
ROA		0.005**
		[2.537]
MTB		0.001***
		[5.300]
Age		0.006
		[1.602]
Sales_growth		0.005***
		[4.537]
Constant	0.291***	0.148***
	[146.374]	[10.558]
Observations	51,166	44,465
Adjusted R^2	0.683	0.696
Firm effects	Yes	Yes
Year effects	Yes	Yes

Notes: The dependent variable in all regressions is firm efficiency. T-statistics, shown in brackets, are robust and clustered at the firm level. Stars, ***, **, *, indicate statistical significance at the 1%, 5%, and 10%, respectively. The definitions of all variables can be found in Appendix Table OA1.

Table 4: Tax Avoidance Channel

	(1)	(2)	(3)	(4)
AI	2.116	1.593	-1.408	-0.309
	[1.445]	[0.830]	[-1.101]	[-0.288]
CASHETR	-0.010***			
	[-2.592]			
AI×CASHETR	-13.372***			
	[-4.060]			
CASHETR_3s		-0.020***		
		[-3.979]		
AI×CASHETR_3s		-11.371***		
		[-2.748]		
CASHETR_adj			-0.010**	
			[-2.506]	
AI×CASHETR_adj			-13.170***	
			[-3.975]	
CASHTAX_NC				-0.138***
				[-3.710]
AI×CASHTAX_NC				-42.183**
				[-2.157]
Size	0.041***	0.043***	0.041***	0.030***
	[13.229]	[12.767]	[13.219]	[12.825]
RD	-0.011***	-0.010***	-0.011***	-0.008***
	[-4.636]	[-3.781]	[-4.630]	[-3.712]
CAPX	-0.015	-0.003	-0.015	-0.001
	[-1.418]	[-0.270]	[-1.428]	[-0.145]
Leverage	0.018*	0.016	0.018*	0.017***
	[1.750]	[1.630]	[1.762]	[2.952]
INTAN	-0.186***	-0.188***	-0.185***	-0.153***
	[-14.140]	[-13.609]	[-14.125]	[-14.630]
ROA	0.167***	0.098***	0.167***	0.015***
	[9.243]	[7.694]	[9.252]	[3.795]
MTB	0.001***	0.001***	0.001***	0.001***
	[5.191]	[4.984]	[5.188]	[6.818]
Age	-0.007	-0.003	-0.007	-0.006
	[-1.360]	[-0.667]	[-1.360]	[-1.260]
Sales_growth	0.014***	0.012***	0.014***	0.005***
	[6.336]	[5.562]	[6.336]	[3.256]
Constant	0.147***	0.136***	0.144***	0.204***
	[7.311]	[6.575]	[7.174]	[12.249]
Observations	33,029	30,173	33,029	44,782
Adjusted R^2	0.706	0.712	0.706	0.674
Firm effects	Yes	Yes	Yes	Yes
Year effects	Yes	Yes	Yes	Yes

Notes: The dependent variable in all regressions is firm efficiency. T-statistics, shown in brackets, are robust and clustered at the firm level. Stars, ***, **, *, indicate statistical significance at the 1%, 5%, and 10%, respectively. The definitions of all variables can be found in Appendix Table OA1.

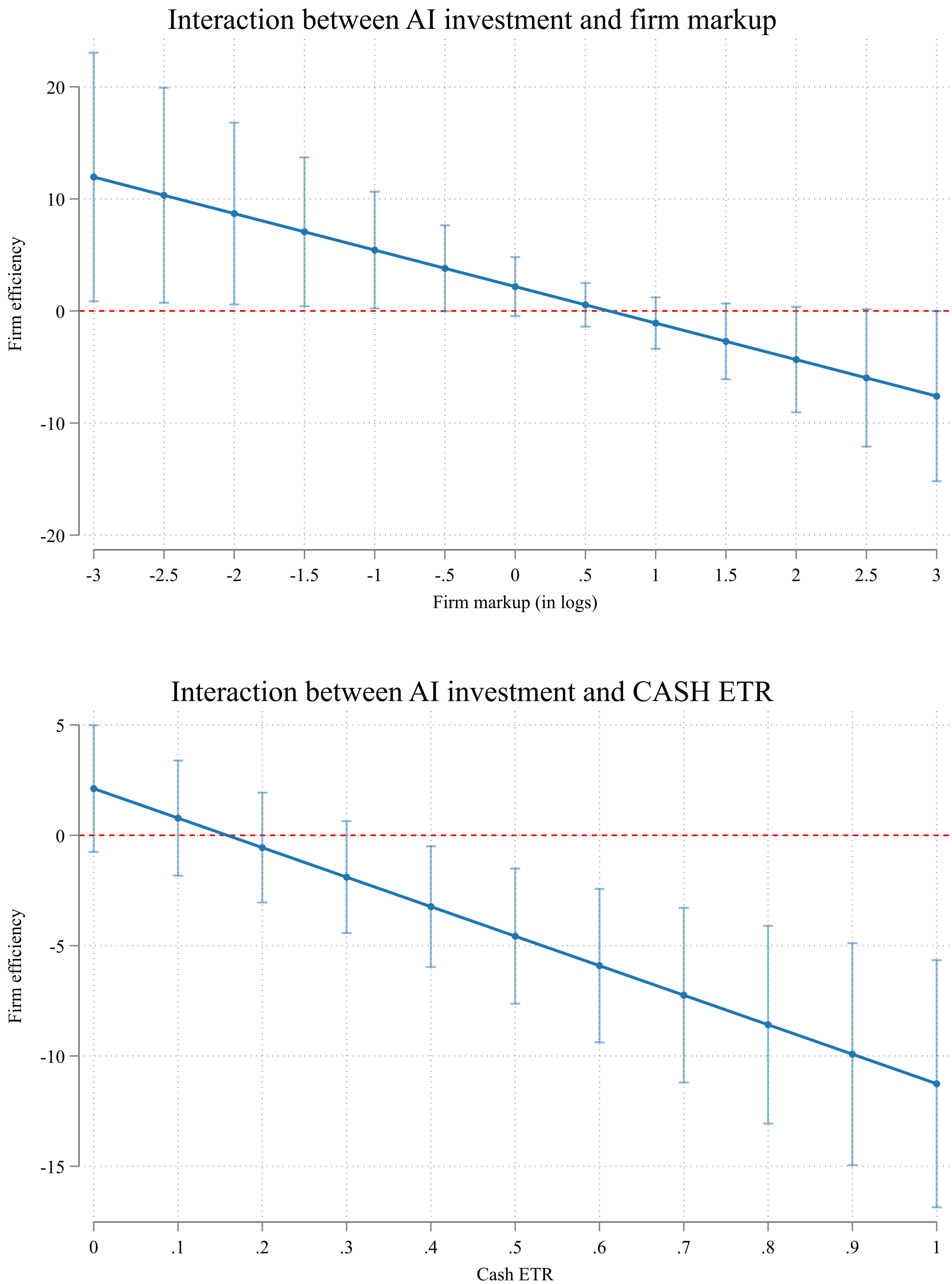

Figure 1: Marginal effects

ONLINE APPENDIX

To accompany the paper:

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Appendix contents

A. Calculation of firm efficiency with DEA

Demerjian, Lev, and McVay (2012) utilize the DEA method to derive firm efficiency. DEA offers two main advantages. First, it ranks efficiency relative to the Pareto frontier, unlike parametric methods that benchmark against the average, which can be skewed by underperformers. Second, DEA avoids imposing arbitrary weights on inputs and outputs, instead deriving them endogenously from the data.

To clarify the procedure, DEA efficiency can be expressed mathematically as the following ratio:

$$\frac{\sum_{i=1}^{s} u_i y_{ik}}{\sum_{j=1}^{m} v_j x_{jk}} \quad k = 1, 2, \ldots, n. \tag{A1}$$

In equation (A1), s denotes the number of outputs, m the number of inputs, and n the decision-making units (DMUs), which in this context are firms. Demerjian, Lev, and McVay (2012) employ one output and seven inputs, all sourced from the Compustat database. Revenue serves as the sole output, while the inputs include: net property, plant, and equipment (PP&E), net operating leases, net R&D, purchased goodwill, other intangible assets, cost of inventory, and selling, general, and administrative expenses (SG&A). For each output and inputs there are weights assigned. These are denoted by u and v, respectively. Bt y and x we denote the quantities of outputs and inputs.

The steps to derive firm efficiency using the DEA technique, are as follows.

1. DMUs are grouped—typically by industry—based on similarities in the relationship between inputs and outputs, ensuring that efficiency is assessed among comparable units.
2. The next step is to maximize equation (A1) for each DMU by changing the weights u and v.
3. The optimal weights obtained are applied to the respective output and input quantities, with the results summed across all outputs (numerator) and all inputs (denominator). This generates a ratio-based efficiency score for each DMU.
4. All efficiency scores are subsequently normalized by the highest score within the group, producing an ordinal ranking of DMUs based on relative efficiency. The most efficient units receive a score of one, indicating optimal performance.
5. By design, the weights u and v are non-negative, reflecting the assumption that all inputs and outputs contribute positively to the production process. Given that the input and output quantities are also non-negative, the DEA efficiency score is bounded below by zero.

The optimization problem that needs to be solved is the following:

$$\begin{aligned} max_v(\theta) = (Sales) \cdot (v_1 CoGS + veSG\&A + v_3 PPE + \\ + v_4 OpsLease + v5R\&D + v_6 Goodwill + v7OtherIntan)^{-1} \end{aligned} \tag{A2}$$

In the equation above, stock variables—such as *Net PP&E, Net Operating Leases, Net R&D, Purchased Goodwill, and Other Intangible Assets*—are measured at the start of year t, whereas flow variables like *Cost of Inventory* and *SG&A* are measured over the course of year t. Demerjian, Lev, and McVay (2012) estimate DEA efficiency separately within each Fama-French industry to ensure that firms being compared share similar business models and cost structures.

B. About the data on AI investment

This section offers additional details on the AI investment measure employed in the analysis. Babina et al. (2024) develop a novel proxy for firms' AI investments by examining the intensity of hiring workers with AI-related skills. Their approach relies on employee resumes to estimate the stock of AI-specialized personnel at each firm for which data is available. To construct this measure, they draw on a large dataset containing over 500 million individual employment profiles obtained from Cognism, a platform that aggregates professional resume data. For further details on the dataset, see Fedyk and Hodson (2023).

Their second data source is Burning Glass, which provides information on over 180 million U.S. job postings from 2010 to 2018. Burning Glass collects data from more than 40,000 online job boards and company websites, employing advanced parsing techniques to structure and aggregate the information into labor market analytics. The dataset is highly granular, including fields such as job title, location, occupation, and employer name. Crucially, each job posting is tagged with a rich set of specific skills. For a comprehensive description of the dataset, see Hershbein and Kahn (2018).

Finally, Babina et al. (2024) construct a human capital–based measure of firm-level AI investment using resume data from Cognism. The process begins by analyzing job postings to empirically identify the skills most closely associated with AI. These AI-related skills are then matched within the resume data to pinpoint AI-skilled workers. Finally, they compute the share of AI-skilled employees at each firm to derive a firm-level measure of AI investment..

C. Additional tables

Table OA1: Variable Definitions

Variable	**Description**
Efficiency	Firm efficiency measure provided by Demerjian, Lev, and McVay (2012) and based on data envelopment analysis.
AI	AI human capital investment is measured as the number of AI-related employees in a given year, scaled by the firm's total number of employees. Source: Babina et al. (2024).
Size	Firm assets (AT) in logs. Source: Compustat.
RD	Research and development expenditures (XRD) in logs. Source: Compustat.
CAPX	Ratio of capital expenditures ($CAPX$) to gross property, plant, and equipment ($PPEGT$). Source: Compustat.
Leverage	Firm leverage. This is calculated from Compustat as $(DLC + DLTT)/AT$.
INTAN	Intangibles (INT) scaled by total assets (AT). Source: Compustat.
ROA	Earnings before interest and taxes divided by total assets (Compustat: $EBIT/AT$).
MTB	Market-to-book ratio (Compustat: $CSHO \times PRCC\_F/CEQ$).
Age	Firms' age in logs. Measured as the number of years since the firm first appears in the Compustat database, including the current year. Calculated by subtracting the initial year of observation from the current year and adding one.
Sales_growth	Based on Compustat's variable SALE, calculated as: $(SALE_t - SALE_{t-1})/SALE_{t-1}$.
Markup	The market power index calculated as in De Loecker et al. (2020). This variable is in logs.
CASHETR	Cash taxes paid ($TXPD$) divided by pretax book income before special items ($PI - SPI$). All values in both the numerator and denominator must be positive. If any value exceeds one, it is capped at one. Source: Compustat.
CASHETR_3s	Sum of cash taxes paid ($TXPD$) in periods t through $t+2$ divided by pretax book income before special items ($PI - SPI$) over the same period. All values must be positive, and values above one are capped at one. Source: Compustat.
CASHETR_adj	Following Balakrishnan, Blouin, and Guay (2019), this variable is defined as the difference between the cash ETR of firm i and the average cash ETR of firms in the same Fama-French 48 industry and asset-size quantile in year t. Source: Compustat.
CASHTAX_NC	Following Henry and Sansing (2018), this variable is defined as the difference between cash taxes paid and 35% of pretax income adjusted for special items, scaled by the market value of assets (computed as: $AT + PRCC\_F \times CSHO - SEQ$). Source: Compustat.

Table OA2: Pearson Correlation Matrix

		[1]	[2]	[3]	[4]	[5]	[6]	[7]	[8]	[9]	[10]	[11]	[12]	[13]	[14]	[15]	[16]
Efficiency	[1]	1															
AI	[2]	0.12	1														
Size	[3]	0.54	0.09	1													
RD	[4]	0.34	0.21	0.38	1												
CAPX	[5]	0.03	0.04	-0.13	-0.01	1											
Leverage	[6]	-0.02	-0.04	0.05	-0.10	-0.12	1										
INTAN	[7]	0.01	0.07	0.22	0.10	-0.06	0.09	1									
ROA	[8]	0.17	0.01	0.28	0.03	-0.02	-0.39	0.03	1								
MTB	[9]	0.09	0.05	-0.01	0.09	0.12	-0.11	-0.01	0.04	1							
Age	[10]	0.15	0.00	0.37	0.14	-0.38	0.05	0.08	0.12	-0.06	1						
Sales_growth	[11]	-0.02	0.00	-0.11	-0.01	0.29	-0.03	0.00	-0.05	0.08	-0.21	1					
Markup	[12]	0.35	0.14	-0.02	0.28	0.16	-0.12	0.11	0.06	0.14	-0.13	0.05	1				
CASHETR	[13]	-0.04	-0.05	-0.02	-0.07	-0.04	-0.02	-0.04	-0.12	-0.06	0.04	-0.11	-0.12	1			
CASHETR_3s	[14]	-0.04	-0.05	-0.05	-0.08	-0.01	-0.05	-0.05	-0.04	-0.06	0.01	-0.04	-0.11	0.56	1		
CASHETR_adj	[15]	-0.03	-0.04	-0.02	-0.05	-0.03	-0.02	-0.04	-0.12	-0.05	0.03	-0.10	-0.08	0.98	0.54	1	
CASHTAX_NC	[16]	-0.16	-0.01	-0.23	-0.04	0.00	0.07	-0.06	-0.50	-0.05	-0.11	-0.01	-0.07	0.77	0.48	0.75	1

Notes: The definitions of all variables can be found in Appendix Table OA1.

Table OA3: Baseline Model with Future Values for the Dependent Variable

	(1)	(2)	(3)	(4)
AI	-1.121	-1.711	-1.738	-2.133
	[-0.972]	[-1.499]	[-1.420]	[-1.626]
Size	0.023***	0.019***	0.016***	0.014***
	[10.000]	[7.963]	[6.600]	[5.623]
RD	-0.009***	-0.009***	-0.008***	-0.007***
	[-4.036]	[-4.097]	[-3.627]	[-2.949]
CAPX	-0.016*	-0.009	-0.012	-0.011
	[-1.720]	[-0.984]	[-1.435]	[-1.288]
Leverage	0.019***	0.018***	0.016***	0.015***
	[4.128]	[3.682]	[3.103]	[2.797]
INTAN	-0.133***	-0.118***	-0.106***	-0.090***
	[-13.188]	[-11.526]	[-9.536]	[-7.522]
ROA	0.008**	0.005*	0.005*	-0.000
	[2.516]	[1.882]	[1.919]	[-0.134]
MTB	0.001***	0.000***	0.000**	0.000***
	[4.427]	[2.919]	[2.379]	[2.918]
Age	0.005	0.006	0.007	0.005
	[1.077]	[1.217]	[1.558]	[1.032]
Sales_growth	0.002*	-0.002	0.001	0.000
	[1.798]	[-1.598]	[0.780]	[0.155]
Constant	0.217***	0.244***	0.257***	0.270***
	[12.791]	[13.770]	[14.279]	[14.398]
Observations	47,485	43,548	39,870	36,496
Adjusted R^2	0.656	0.662	0.666	0.669
Firm effects	Yes	Yes	Yes	Yes
Year effects	Yes	Yes	Yes	Yes

Notes: In column (1), the dependent variable is firm efficiency measured at year $t+2$; in column (2), at $t+3$; in column (3), at $t+4$; and in column (4), at $t+5$. T-statistics are shown in brackets and are robust to heteroskedasticity with clustering at the firm level. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively. The definitions of all variables can be found in Appendix Table OA1.

Table OA4: Baseline Results by Industry

Variables	Mining (1)	Construction (2)	Manufacturing (3)	Transportation (4)	Wholesale (5)	Retail (6)
AI	7.318	-30.305***	1.445	-0.977	-1.326	6.024
	[1.052]	[-3.616]	[1.012]	[-0.238]	[-0.595]	[0.688]
Size	0.006	0.044***	0.033***	0.027***	0.069***	0.048***
	[0.702]	[2.796]	[8.140]	[3.008]	[5.213]	[6.142]
RD	0.010	0.017	0.000	-0.013	-0.001	-0.023
	[0.545]	[0.992]	[0.135]	[-1.255]	[-0.124]	[-1.389]
CAPX	0.042	0.080	0.013	-0.047	-0.028	-0.007
	[0.982]	[1.670]	[0.972]	[-1.350]	[-1.074]	[-0.198]
Leverage	0.027	0.009	0.030***	0.002	0.009	0.036**
	[1.348]	[0.449]	[3.721]	[0.164]	[0.244]	[1.989]
INTAN	-0.278***	-0.149*	-0.176***	-0.188***	-0.137**	-0.196***
	[-3.935]	[-1.902]	[-11.421]	[-4.626]	[-2.383]	[-4.486]
ROA	0.050**	-0.003	0.025***	0.006	0.027	0.044***
	[2.210]	[-0.448]	[4.845]	[0.754]	[1.184]	[3.229]
MTB	0.000	-0.000	0.001***	-0.000	0.000	0.000
	[0.782]	[-0.169]	[5.900]	[-0.287]	[0.326]	[1.113]
Age	0.000	-0.085***	0.011*	-0.036**	-0.017	-0.014
	[0.011]	[-2.999]	[1.936]	[-2.099]	[-1.056]	[-0.995]
Sales_growth	0.010**	0.019***	0.003	0.005	-0.001	0.000
	[2.533]	[2.994]	[1.407]	[0.883]	[-0.109]	[0.022]
Constant	0.292***	0.284**	0.115***	0.280***	0.014	0.096
	[4.939]	[2.232]	[4.506]	[3.863]	[0.178]	[1.616]
Observations	2,660	762	26,887	3,404	2,095	3,915
Adjusted R^2	0.534	0.663	0.672	0.623	0.708	0.712
Firm effects	Yes	Yes	Yes	Yes	Yes	Yes
Year effects	Yes	Yes	Yes	Yes	Yes	Yes

Notes: The dependent variable in all regressions is firm efficiency. T-statistics, shown in brackets, are robust and clustered at the firm level. Stars, ***, **, *, indicate statistical significance at the 1%, 5%, and 10%, respectively. The definitions of all variables can be found in Appendix Table OA1.

Table OA5: Results for Firms with Positive AI Employment in Year 2007

	(1)	(2)	(3)	(4)	(5)	(6)
AI	1.219	10.144***	2.298	4.947	-0.794	1.983
	[0.418]	[2.664]	[0.611]	[1.205]	[-0.233]	[0.607]
Markup		0.121***				
		[3.007]				
AI × Markup		-10.136**				
		[-2.180]				
CASHETR			-0.024			
			[-0.829]			
AI × CASHETR			-11.767			
			[-1.371]			
CASHETR_3s				-0.023		
				[-0.571]		
AI × CASHETR_3s				-12.629		
				[-1.346]		
CASHETR_adj					-0.019	
					[-0.639]	
AI × CASHETR_adj					-14.049	
					[-1.638]	
CASHTAX_NC						-0.510
						[-1.564]
AI × CASHTAX_NC						50.427
						[0.607]
Size	-0.014	-0.011	-0.003	-0.002	-0.003	-0.012
	[-0.907]	[-0.712]	[-0.138]	[-0.077]	[-0.144]	[-0.717]
RD	-0.010*	-0.006	-0.029***	-0.025***	-0.028***	-0.019**
	[-1.718]	[-0.942]	[-3.515]	[-3.120]	[-3.514]	[-2.096]
CAPX	-0.053	-0.049	-0.142*	-0.094	-0.145*	-0.030
	[-0.979]	[-0.932]	[-1.868]	[-1.407]	[-1.891]	[-0.541]
Leverage	0.074***	0.075***	0.077***	0.063***	0.077***	0.080***
	[3.146]	[3.483]	[3.225]	[2.895]	[3.222]	[3.391]
INTAN	-0.164***	-0.209***	-0.194***	-0.200***	-0.194***	-0.141**
	[-2.678]	[-3.084]	[-2.901]	[-2.893]	[-2.904]	[-2.273]
ROA	0.076**	0.024	0.127	0.078	0.127	0.043
	[2.199]	[0.745]	[1.554]	[0.939]	[1.556]	[1.012]
MTB	0.001*	0.002*	0.001	0.001	0.001	0.000
	[1.801]	[1.838]	[0.804]	[0.649]	[0.797]	[0.645]
Age	-0.061	-0.028	-0.070	-0.092**	-0.069	-0.069
	[-1.418]	[-0.688]	[-1.499]	[-2.175]	[-1.484]	[-1.571]
Sales_growth	0.040***	0.018	0.043	0.033	0.043	0.031**
	[3.178]	[1.606]	[1.509]	[1.182]	[1.531]	[1.989]

Table OA5 – continued on next page

Table OA5 – continued from previous page

	(1)	(2)	(3)	(4)	(5)	(6)
Constant	0.902***	0.682***	0.946***	0.984***	0.939***	0.932***
	[4.972]	[3.825]	[4.481]	[4.710]	[4.465]	[5.038]
Observations	2,311	1,896	1,851	1,627	1,851	2,118
Adj. R^2	0.706	0.715	0.714	0.726	0.714	0.709
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes

Notes: The dependent variable is firm efficiency. T-statistics are reported in brackets. Standard errors are clustered at the firm level. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively. The definitions of all variables can be found in Appendix Table OA1.