AI Technologies and Business Value: Quantifying the Monetary Effects of AI Adoption in Firms

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Abstract

This project uses 2023 cross-sectional firm-level data on technologies in use from S&P 500 companies to estimate a quantifiable benefit of using AI for a business, an essential question in today's world, but yet overlooked due to its recent emergence. Aggregate effects, intensive margin effects, and sector-specific effects are estimated by modeling firm value through a Cobb-Douglas OLS model with AI technologies as a factor of production. Controls include other factors of production and firm-specific characteristics to mitigate the effects of simultaneity and omitted variable bias. The findings suggest that a 1% increase in a firm's AI adoption can be linked with an average of 0.17% increased business value. This rises to 0.2% and is more strongly observed among firms already using AI. The Healthcare, Energy, Utilities, Financial, and Real Estate sectors show sensitivity to AI adoption. An interpretation and discussion of the results is provided. This paper acts as a first step in the firm-level measurement of how AI affects value indicators, hoping that over time and with more data, a much more precise estimate and comprehensive view will be gained.

Keywords: *artificial intelligence, business, innovation, AI adoption, technology*

I. Introduction

ARTIFICIAL intelligence (AI) has taken the world by storm: early work in the field dates back to the 1950s, but only advances in recent years saw the technology become widespread, accessible, and more applicable to daily life. Worldwide search popularity for "artificial intelligence" increased by 736% since February 2021, with the largest growth emerging after ChatGPT's release on November 30th, 2022 ("Google Trends", 2023). Global labor markets and the skills demanded by companies are undergoing a shift, as the share of job postings related to AI increased across almost every sector in the United States and other developed economies since the 2010s (Maslej et al., 2023). Nations are drafting regulations, with the EU's recently approved AI Act becoming the world's first set of government guidelines aimed at "ensuring [large, powerful AI models] do not present systemic risks" and providing "strong safeguards [...] against any abuses of technology by public authorities" (Tudorache, 2023). Educational institutions are exploring and adapting to the new advances, with NYU Abu Dhabi testing ChatGPT's exam and homework performance across 32 university courses and comparing it to students' grades (Rahwan and Zaki, 2023).

In the professional world, AI already found itself many applications and is disrupting the way business is carried out. Firms are increasingly integrating AI solutions for a variety of purposes in their business models, in hopes this will benefit them in cost optimization, revenue generation, and improved efficiency (Enholm et al., 2022). Annual corporate investment in 2022 slowed down compared to its record high in 2021, yet still soared at almost double that of 2018 and 18 times that of 2013 (Maslej et al., 2023). Companies using AI are reportedly seeing their desired returns and intend to increase their investments in the years to come (Chui et al., 2023a).

It is evident that, as AI is growing in popularity, the study of the subject becomes increasingly important. The implications of research on the potential uses, benefits, and weaknesses of AI are very relevant at the economy, country, academic, and firm levels. However, its study remains scarce, as the technology is still relatively young. Particularly, there is a lack of firm-level investigations, which could grant insights into the true usefulness of AI for the economy (Seamans and Raj, 2018). Available literature either limits itself to conceptual frameworks or reviews, remains at the country or industry level, follows a single non-replicable data collection effort, or does not agree on a quantified measure for the impacts of AI technologies on firm outputs.

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If data is used, it is often based on survey responses (see Chui et al., 2022; Chui et al., 2023a), which provide insights into the perceived usefulness of AI on profits rather than any actual correlations between the two. Reports using data from such private investigators often omit their methodologies, making their publications non-replicable and non-transparent from the academic front. Plus, data sets from such firms are often kept private, as respondents may be protected under client confidentiality agreements. Overall, the few data-driven investigations currently available cannot be built upon by academics, and independent data collection efforts may be difficult to carry out given the general reluctance of businesses to publish their internal information. There is a clear need for a reusable, public, data-driven, and academically tested methodology for studying the impacts of AI technologies at the firm level.

This paper contributes to current literature by providing a first attempt at a non-survey dataset and methodology for the quantification of AI benefits for the financial outcome of businesses. This is done by using available insights on the study of innovation in firms to create a robust model, which we use to correlate a private database of company technologies with public financial metrics. This cross-sectional research provides two major contributions: a re-usable and upgradable methodology for investigations on firm-level AI impacts, and a first attempt at quantified metrics for overall business benefits and intensive margins of AI technologies. We hypothesize that AI should have a positive impact on value and that adding more technologies to a firm should continue to bring positive benefits. As a secondary research question, we explore the sector-specific effects of AI on firms, highlighting which industries are most sensitive to AI technology benefits.

Despite the general scarcity of literature on the subject, this paper finds a concise review focused on creating an appropriate methodology for non-survey data exploration on the topic. Insights from private investigators, data-driven efforts with specialized scopes, and research from past market shocks related to innovation are collected to guide this paper's model. Simultaneity, or the simultaneous causality of the dependent and independent variables, appears to be a common challenge in the study of innovation and technological revolutions in firms. Namely, the decision to invest in and apply AI technologies could both drive and be driven by high business performance coming from the achievement of high profits (Czarnitzki et al., 2022). Control variables inspired by multiple literature sources, including supplementary factors of production and firm-specific factors, are used to mitigate this effect as well as omitted variable bias. Furthermore, robust standard errors are applied to support the model against the above and heteroskedasticity. Unobserved heterogeneity may also be relevant to address, as firms that use AI may be substantially different from those that do not. Investigating the intensive margin removes this difference and provides additional insights.

The resulting methodology is a Cobb-Douglas cross-sectional OLS regression model that considers AI technologies as a factor of production in firms. This paper is one of the first to use non-survey data to explore the financial benefits of AI on business, providing a starting point for future research. With further contributions and more data, the hope is to provide a first step towards a more precise estimate and comprehensive view of the benefits of AI to the professional world.

II. Literature Review

1. Current AI Trends in Business

Artificial intelligence trends are an increasingly popular research subject for both private researchers and formal academic institutions. However, the lack of a coordinated approach between the two sides creates a knowledge vacuum for firm-level replicable research. It is useful to explore existing research contributions from both mainstream private investigators and academic sources to gain a holistic view of the current state of AI in business, as well as the gaps in currently available literature.

McKinsey & Co. is the major research contributor thanks to its yearly Quantum Black survey reports (see Chui et al., 2022; Chui et al., 2023a). They track AI adoption and trends, finding that the share of firms that claim to use AI has been above 50% since 2019. Based on their 2022 survey results, about 59% of firms perceive revenue increases powered by AI, with Manufacturing, Marketing & Sales, and Risk companies seeing the most benefit. 42% of respondents also report cost decreases, particularly in the Manufacturing and Service Operations industries. The average number of AI capabilities used by organizations has doubled from 1.9 in 2018 to 3.8 in 2022 (Chui et al., 2022). Private investment in AI peaked in 2021 and steadied around $100 billion in the last two years (Chui et al., 2023) driven by the ascent of generative AI, which alone produced investments of $25.2 billion in 2023 (Maslej et al., 2024).

Generative AI refers to technologies such as ChatGPT and Stable Diffusion, able to independently create content through various media. It is an emerging and popular solution for automating repetitive tasks which gives workers more time to focus on their human-centered capabilities (Chui et al., 2023b). 79% of McKinsey's respondents in 2023 reported being exposed to generative AI technologies, with 22% actually applying it in their workplace operations (Chui et al., 2023a).

However, while these findings may seem comprehensive, private company reports such as McKinsey's do not share their samples and methodologies with the public. For instance, report readers have no access to the questions included in the survey or the list of firms surveyed. Sensitive firm-level information such as surveyed company names may often be protected under confidentiality agreements, especially if the companies are somehow affiliated with the owner of the survey. Replicability and transparency are important for academics and institutions to build on a given body of research and ensure the produced knowledge is defensible, consistent, and coherent (Dewald et al., 1986).

Using McKinsey's survey results and other sources, Stanford University's Institute for Human-Centered AI publishes a yearly "AI Index" report including business trends as well as AI research, ethics, public opinion, and sector applications such as science and medicine (see Maslej et al., 2023; Maslej et al., 2024). As part of their analysis of the economic impacts of AI, they collect insights on the impact of Microsoft Copilot (a generative AI productivity tool) on task completion across information retrieval, content creation, meeting minutes, and more (also see Cambon et al., 2023). Depending on the type of work they were assigned, Copilot users completed their tasks 26% to 73% faster than the non-AI control group. On the other hand, mixed or inconclusive evidence was found when comparing the quality of produced work. Overall, businesses are seen to be actively engaged in AI technologies and advancements, especially larger ones. Maslej et al. (2024) also highlight that nearly 80% of all Fortune 500 companies mentioned the term AI in their 2023 earning calls, with the most frequent references being made to generative AI.

The Stanford AI Index does a better job at transparency and public access than McKinsey, with data sources including research institutes, think tanks, and published papers alongside the more common private company surveys. However, while including figures data on a public Google Drive folder is better than no transparency at all, there are still very few insights on the methods used to generate said data or on robustness checks to ensure validity.

Academic literature, albeit scarce, reinforces and enriches the consensus that AI benefits corporations provided by the above mainstream research. Nafizah et al. (2023) focus their scope on the effects of AI and machine learning on micro-enterprises, finding that early adopters (or first movers) of machine learning experience a significant benefit on innovation capabilities. They highlight that second and late movers see reduced impacts, implying that a first-mover strategy seems to be successful in micro enterprises looking to gain an advantage with AI and machine learning technologies.

Furthermore, Enholm et al. (2022) provide a systematic literature review focused on AI and businesses. They explore how technological readiness, organizational aspects, and environmental factors play a role in a firm's ability to harness AI to either automate certain work or empower humans in doing theirs. They further categorize the impacts of AI technologies into first-order (process) and second-order (firm) effects, the latter of which is claimed to be indirect and stemming from other first-order effects. Process-level effects include efficiency, insight generation from large bodies of data, and business process transformation and innovation. Following from these, second-order effects include the raising of revenues, the reduction of costs, and the enhancement of efficiency resulting in improved operational, financial, market, and sustainability performance.

Enholm et al. (2022) also include a discussion on the possible negative or unintended effects of AI in firms, with possible causes including the lack of governance practices or insufficient transparency in AI systems. For instance, algorithmic bias may occur if a model or its training data are not properly checked, which in turn could cause discrimination, inaccuracy, and possible damages to a company's image and revenues. If a piece of AI technology is found to have low explainability and transparency by the public, trust in it would be weak and its adoption by firms and consumers would greatly reduce.

Overall, some academic research on the study of the business impacts of AI have been made, but are either specific to a certain scope or are not data-driven. While literature reviews and focused explorations are helpful, the need is clear for a research method that balances the firm-level approaches of private investigators with academic rigor and replicability.

2. Methodology for the Study of AI in Businesses

The above literature gives an overview of AI trends as seen from private investigators and some academic sources. Unfortunately, data-driven efforts that apply an econometric solution to measuring AI benefits are quite scarce. For the few that are currently available, we explore two relevant investigations that will help the creation of our own methodology.

Czarnitzki et al. (2022) present a study with a similar topic and motivation to this paper: to quantify the impact of AI adoption on the productivity of German enterprises. The literature they analyze presents divergent viewpoints regarding AI, with proponents asserting its potential to enhance corporate productivity through automation, innovation, and innovative ideas (Agrawal et al. 2019; Cockburn et al. 2019), and skeptics refuting these claims by emphasizing the general slowdown of innovation and economic growth despite high efforts (Gordon, 2018; Bloom et al., 2020). Furthermore, they highlight that research on proxies like AI patents or robotics fails to capture the complete range of possibilities that AI offers for businesses, and stress the significance of studying actual AI adoption even though data on this topic is scarce (Seamans and Ray, 2018; Brynjolfsson et al., 2017).

Driven by this, their paper's model presents an effective framework for the analysis of AI using data at the level of individual firms. The authors encounter a variation of the Mannheim Innovation Panel, the German contribution to the EU-wide Community Innovation Survey (Peters and Rammer, 2023). This is a well-studied survey that produced multiple studies on AI and innovation for German firms (see Rammer et al., 2022). The survey includes questions on the use of AI, encompassing a wide array of AI categories and their respective commercial applications. From these and other supplementary questions on innovation and firm-specific information, they derive data on AI-using firms, their AI intensity, research and development (R&D) frequency, and other controls.

They utilize a Cobb-Douglas production function to represent business productivity, incorporating AI technology as a factor of production as discussed by Aghion et al. (2019), Zeira (1998), and Acemoglu and Autor (2011). Their measurement of firm production is based on annual sales, which may not fully reflect the range of benefits provided by AI since it does not consider cost reductions (Enholm et al., 2022). Their approach to firm total factor productivity (TFP) employs variables created from survey questions including R&D and past technological improvements, as well as a firm's age. Access to the techniques derived from their primary dataset is challenging. Our project uses the same Cobb-Douglas theoretical framework for guiding our empirical approach, but we use a non-survey database for firm-level information.

Czarnitzki et al. also flag some critical challenges with the practice of comparing firm technologies and value. The first is endogeneity, or simultaneity as we define it, from the possibility that a firm's decision to invest in AI technologies may result from a period of high profits. The second is omitted variable bias, which could arise from the connection of a firm's adoption of AI with other factors such as digitalization campaigns or the general expansion of a firm's IT infrastructure.

The authors address these challenges employing instrumental variables (IVs) created using the survey's questions and other panel data. These IVs include industry-level density of AI-using firms, average annual innovation expenses per employee, and resistance to innovation activities within firms. They find positive marginal effects of AI IVs on sales, which have a large range between 5% and 47%. To add to their IV regressions, they also use panel data for 2017 and 2018 where they again find a marginal effect of around a 5% increase in sales due to AI use. Finally, they apply entropy balancing as a tool to mitigate unobserved heterogeneity bias: they increase the weight of non-AI users that have similar levels of the other production factors relative to more divergent ones, helping to maintain relevant information in the pre-processed firms.

Regrettably, the questionnaire and dataset utilized in the study were not replicated for the following years. However, the use of firm-specific factors such as a firm's propensity to invest in AI or the state of its overall IT infrastructure as control variables can enrich the robustness of our investigation and provide a strong foundation for this paper's model.

In the absence of data-driven studies on AI and firms such as Czarnitski et al., we look towards research on innovation-related singularities and their impact on the business world. Arslan and Ozturan (2011) look into the impacts of IT and the Internet in the workplace during its market shock in the 2000s. They argue that simply investing in IT is insufficient to justify a strategic advantage. Instead, they propose that these technologies should reinforce the fundamental strengths of the company and be in harmony with both human and complementary resources to generate value.

Their motivation is aligned with a larger research stream sparked by the Solow Paradox of the 1970s-80s, in which "the computer age [was] seen everywhere but in the productivity statistics", and particularly its recent renewal in the last two decades (Solow, 1987). This is a similar critique from the aforementioned Gordon (2018) and Bloom et al. (2020), showing how the study of AI in the economy is similar and closely connected to that of past innovation breakthroughs.

Building on a resource-based model by Ravichandran and Lertwongsatien (2005), Arslan and Ozturan

(2011) extend their methodology to include complementary assets, an updated measure of IT stock, and stronger controls for firm-specific factors. They use data from a self-conducted survey, which unfortunately only produced 36 responses out of their sample of 212 firms. What is interesting in this study is the purpose of their control variables. Particularly, they include firm age and firm size to account for omitted variable bias. First, they argue that firm age can represent how well a company works as an organization through maturity in internal processes and stronger interfirm relationships, impacting firm performance. Second, they consider firm size, since firms with more employees may have more resources that could help them use IT more efficiently than smaller ones. In the Cobb-Douglas model, this would be included in the measure for labor as a factor of production. They also control for industry IT intensity, since some sectors value information and digital services more than others. While data on this control is not widespread, it would fit this paper's secondary research question on the sector-based benefits of AI.

III. Methodology & Data

The methodology resulting from the literature is a Cobb-Douglas cross-sectional linear regression. Firm output Y_i is represented through its factors of production: capital K_i , labor L_i (which also controls for firm size), intermediate inputs including goods and materials M_i , total factor productivity A_i (data for which is discussed below), and the variable of interest AI_i representing the amount of AI technologies used:

$$Y_i = A_i K_i^{\alpha_K} L_i^{\alpha_L} M_i^{\alpha_M} AI_i^{\alpha_{AI}} \tag{1}$$

From this, we apply the commonly used log-transformation, add the non-production factor control *age* as suggested by Arslan and Ozturan (2011), and include the error term:

$$\ln Y_i = \ln A_i + \alpha_K \ln K_i + \alpha_L \ln L_i + \alpha_M \ln M_i + \alpha_{AI} \ln AI_i + age_i + \epsilon_i \tag{2}$$

The coefficient of interest is AI, interpreted as a percentage change in Y_i per 1% change in AI_i.

When considering firm samples, established stock indices such as the S&P 500 index stand out as comprehensive and representative lists of companies that show diversification in both industry and company sizes (Beers, 2023). Firm-level data for these is easily accessible and mostly well-reported. Using the S&P 500 list (which includes 500 companies) would allow the model to cover the US economy, a considerable contribution to the literature on the topic. Yet, one downside is the exclusion of small and mid-capitalization companies, for which data is unfortunately less widespread despite making up a large portion of the US economy and labor market (Downing and Garcia, 2021). This highlights an opportunity for further exploration in which the model is tailored to include SMEs and where comparisons of AI benefits versus large-cap companies can be made. This paper will use the S&P 500 firm list as of data collection in October 2023.

When assessing the full model, White's Test for heteroskedasticity was used and returned positive. This further justifies the use of robust standard errors, which we apply to all regressions. Additionally, simultaneity may be present with our approach, visible by observing if Y_i has any effect on AI_i. Using IVs (the conventional method to address this issue) would be challenging with the limited firm-level data available and without a baseline methodology for the topic, which this paper aims to provide. While this model only mitigates bias through control variables and robust standard errors, we allow for additional contributions and more specialized methods to develop from it.

1. Data & Sources - AI-Related Variables

The paper's independent variable is the amount of AI technologies used by a company. This rare but critical dataset is provided by D&B Hoovers, a business intelligence company that offers firm-level insights on the specific types of hardware and software that a company is known to use within its technology stack (Dun & Bradstreet, 2022). They provide a list of "technologies in use" that names the specific pieces of software/hardware used by firms categorized by type and subtype. This list is available for a large number of US firms but not for foreign firms, supporting the decision to focus on S&P 500 firms. While D&B Hoovers does not specify a time period for this data, it is assumed it represents firms as of data collection in the year 2023.

We scrape the amounts of technologies falling under the header "Artificial intelligence" and subheader "Data science & machine learning" for each firm. We also record the sum of a firm's total technologies in the list, used to calculate non-AI technologies representing TFP levels for each firm. This is a more direct approach to controlling for non-AI productivity than previous literature. For example, Apple Inc. is seen to use 2 "Artificial intelligence" and 6 "Data science & machine learning" technologies out of a total of 1,375, leaving 1,367 non-AI technologies. Summary statistics are provided in Table 4.

On average, firms in the sample have between 3 and 4 AI technologies and between 995 and 996 non-AI technologies. These two measures are so substantially different in the sample because non-AI technologies include a wide array of productivity-boosting tools ranging from "customer relationship management systems" to laptops and mobile phones, while AI technologies are strictly limited to plain AI tools, machine learning, or AI-powered data science. We can also observe the differences between firms in the sample, varying so greatly in size, age, and sectors that the range of non-AI technology expands from 3 to 4007, while the smaller (yet still relevant) range of AI technology spans between 0 and 14.

Since the model uses logarithms and about 10% of the sample has an AI technologies value of 0, this variable will be increased by 1 to allow for ln AIi to be well-defined. A firm with no AI will have its value adjusted to 1, meaning ln AIi for that firm will equal zero. This is consistent with non-AI-using firms having zero effect from using AI, showing this transformation does not impact the interpretation of the model.

2. Data & Sources - Financials and Control Variables

Financial data for our outcome variables is much more publicly available and easily accessible for almost all of the firm sample. Thanks to this, we can extract eight different financial value metrics for a wide array of results: revenues, gross profits, net income, retained earnings, enterprise value, EBIT, EBITDA, and earnings per share. We choose to avoid stock prices and share-related value metrics to ensure our results are not tainted by the effect of speculation or other events that are unrelated to firm productivity and profitability.

We use Capital IQ, a database maintained by Standard & Poor's, and its Excel integration to select and extract data spanning over a 12-month period ending in January 2024. This ensures financials will reflect firm operations from the year 2023. Most metrics are in $USD millions, except earnings per share which is in $USD. Summary statistics are shown in Table 5. Once again, great variation can be seen in the firm sample.

Control variables were also gathered through Capital IQ for the same time period. Again, most are shown in $USD millions, except for firms' founding year (which is used to calculate firm age by subtracting from 2023) and number of employees (which will control for both labor and firm size). Intermediate inputs are represented with Cost Of Goods Sold (COGS) instead of a measure of inventory or raw materials because of the latter's inconsistent reporting across firms. Table 6 shows control variables summary statistics.

3. Data & Sources - Sectors

We use the industry sector classification of 11 categories provided by Capital IQ. Table 7 shows the sector composition of the firm sample as well as summary statistics on the AI distribution by sector. The sectors with the most representation are Industrials (15%) and Financials (14.5%), the least represented are Communications (3.9%) and Energy (4.7%). Real Estate firms have the lowest average amount of AI technologies at 1.31, while Communications firms have the highest at 6.26. In fact, Real Estate shows the largest number of non-AI-using firms at 11, followed by Financials at 6.

The number of observations for individual sectors are quite small, with five bins reaching 30 firms or below. To avoid sector regressions having too few observations and therefore producing weak results, we employ a pairing system by sector similarity (including the type of work, type of clients, technologies used, business environments, regulatory frameworks, etc. . .). Table 8 shows the new composition by bin pair, in which we indeed see more comparable observation amounts for all bins. The Energy + Utilities pair shows the lowest average AI technologies at 2.74, while Communications + IT has the highest at 4.81. The pair with the highest number of non-AI-using firms is still Financials + Real Estate with 17. Figure 4 illustrates the distribution of AI technology broken down by sector pair, which again shows the difference in AI adoption across sectors.

IV. Results & Discussion

1. Exploratory Analysis & Comparisons

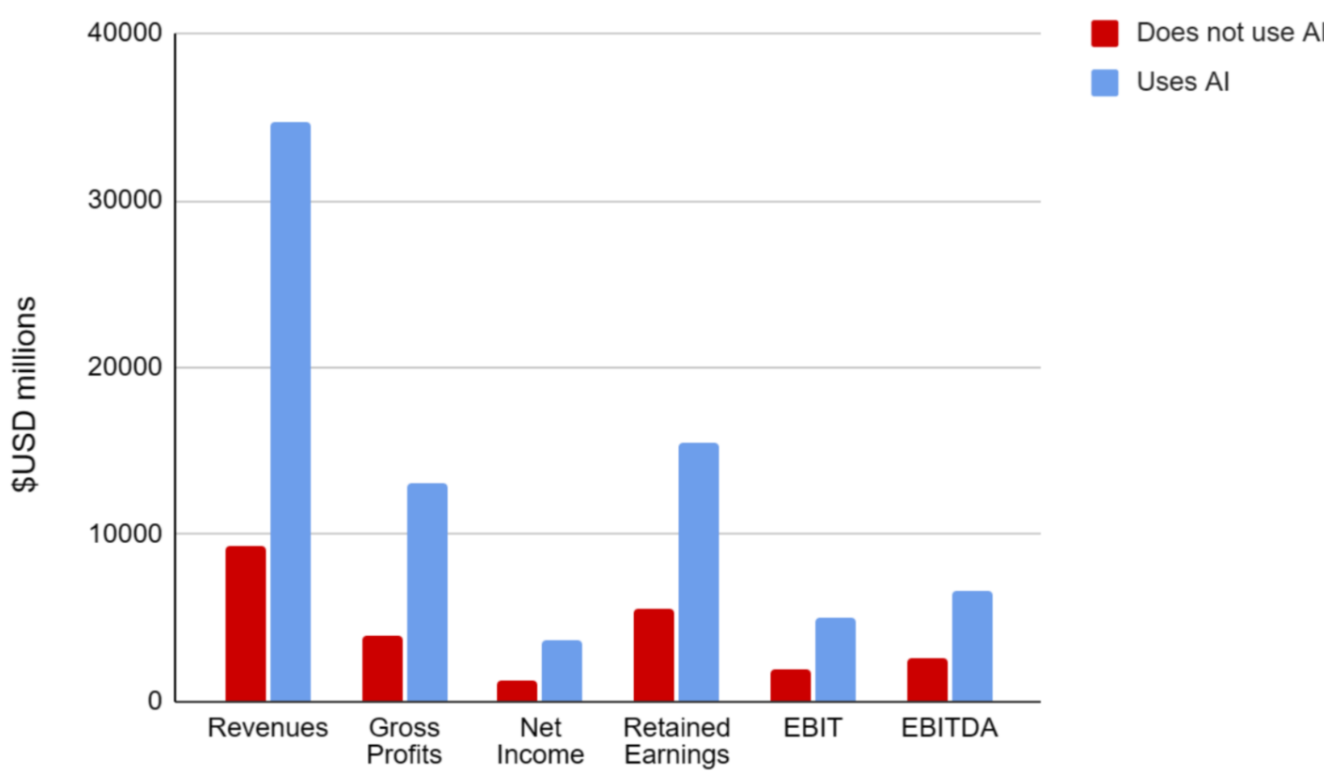
A first exploration of the data reveals a positive overarching connection between value and AI adoption. The correlations shown in Table 1 range from 0.11 to 0.43 and point to a promising positive relationship. Two firms act as outliers for EPS, but the correlation remains weak when they are excluded.

Table 1: *Correlations of Value to AI*

Value Variable	AI Technologies
Revenues	0.14
Gross Profits	0.43
Net Income	0.31
Retained Earnings	0.29
Enterprise Value	0.31
EBIT	0.34
EBITDA	0.38
Earning Per Share	0.11

The above positive link is reinforced by a surface-level comparison of business value averages across firms that do not use AI versus those that do. Figure 1 shows that AI-using firms tend to be correlated with higher average financial outcomes compared to non-AI-using firms.

Figure 1: *Business Value Averages and AI Use*



Enterprise value and EPS were removed for graph clarity, but they also follow the same pattern. While we cannot interpret this analysis as causal due to simultaneity and lack of controls, it provides good descriptive context on the intrinsic differences between AI-using and non-AI-using firms. The discrepancy for AI-using versus non-AI-using firms is evident, but varies in magnitude across financial outcomes. Naturally, this insight is based on correlation alone.

II. Main Results - Aggregate Effect

To investigate causality, we now run our model on the eight outcome variables across the full dataset of firms. Table 2 shows the results of the eight regressions. The Variance Inflation Factor (VIF) test was done and no variables displayed VIF values above the recommended threshold of 10 (Wooldridge, 2008), showing little impact from multicollinearity on robustness.

The coefficient of interest returned positive for all eight value metrics, suggesting a trend that AI technologies are correlated with higher business value. Of these, three show significant results, providing statistical evidence in favor of the trend. Significant coefficients yield an average value increase of 0.17% for a 1% increase in AI adoption. Scaling this up, a 100% increase in adoption (or doubling of a firm's current AI capabilities) is

Table 2: *Aggregate Results*

	(1) ln (Revenue)	(2) ln (Gross Profits)	(3) ln (Net Earnings)	(4) ln (Retained Earnings)	(5) ln (Enterprise Value)	(6) ln (EBIT)	(7) ln (EBITDA)	(8) ln (Earnings Per Share)
ln (AI Tech)	0.10***	0.16***	0.24***	0.22	0.11	0.08	0.08	0.10
	(0.04)	(0.06)	(0.08)	(0.15)	(0.07)	(0.08)	(0.06)	(0.12)
ln (Non-AI Tech)	0.05	0.04	-0.17**	-0.10	0.00	-0.07	-0.08	-0.23
	(0.04)	(0.06)	(0.07)	(0.15)	(0.06)	(0.07)	(0.07)	(0.15)
ln (Labor)	0.06**	0.18***	0.10**	0.22***	0.22***	0.09**	0.07**	0.10*
	(0.02)	(0.03)	(0.04)	(0.08)	(0.03)	(0.04)	(0.03)	(0.05)
ln (Capital)	0.25***	0.52***	0.53***	0.55***	0.62***	0.56***	0.66***	-0.08
	(0.03)	(0.03)	(0.05)	(0.08)	(0.04)	(0.05)	(0.04)	(0.08)
ln (Int. Input)	0.59***	0.11***	0.15***	0.07	-0.10***	0.17***	0.16***	0.13**
	(0.03)	(0.03)	(0.04)	(0.07)	(0.04)	(0.04)	(0.03)	(0.05)
Firm Age	-0.00**	-0.001*	0.00	0.00***	-0.00***	0.00	0.00	0.00
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Constant	0.91***	0.30	0.72	0.77	3.32***	0.21	-0.07	1.64
	(0.23)	(0.36)	(0.51)	(0.91)	(0.44)	(0.51)	(0.44)	(1.17)
Observations	466.00	464.00	434.00	311.00	459.00	450.00	454.00	434.00
R-squared	0.93	0.75	0.58	0.46	0.61	0.58	0.76	0.05

Note: The model was run on 8 outcome variables for the full dataset of firms. *ln(AI Tech)* is the natural log of the amount of AI technologies used in a company. Before running the model, a unit was added to ln(AI Tech) to ensure the logarithm is fully defined including in the case when a firm has zero AI tech. Similarly, *ln(Non-AI Tech)* is the natural log of the non-AI technologies, calculated by subtracting AI tech from the number of total pieces of tech in a firm. This was not adjusted for the logarithm since there were no firms with zero non-AI tech. Observations fluctuations are due to missing or misreported financial data.
Robust standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1

linked with a 17% increase in value. This confirms our hypothesis and the general literature consensus that AI technologies impact firms positively. Some details worth noting are the elevated R-squared pointing to the high explanatory power of the model, the predictably positive and significant effects of labor, capital, and intermediate inputs, and the surprising outcome of a largely insignificant and negative coefficient for TFP.

Firm age seems to have an impact near zero, oscillating between positive and negative. The literature provides conflicting evidence for the sign of such an effect (see Czarnitski et al., 2022; Coad et al., 2013), possibly caused by the differences in the classification of young versus old firms or the use of the log transform. We do not take the log of age since we do not include it as a factor of production in our Cobb-Douglas function, which other literature may do.

III. Main Results - Intensive Effect

We enrich our analysis with an exploration of the intensive margin, aiming to explore whether adding more AI technologies to a firm already using AI continues to bring additional benefits. We repeat our eight regressions but only on firms with non-zero amounts of AI technologies. Again, no multicollinearity was detected from the VIF test. Table **??** shows the results. We follow the plotting guidelines from Kane (2023) and Jann (2014) to compare the results of Table 2 and Table **??** in Figure 2.

Table 3: *Intensive Margin Results*

	(1) ln (Revenue)	(2) ln (Gross Profits)	(3) ln (Net Earnings)	(4) ln (Retained Earnings)	(5) ln (Enterprise Value)	(6) ln (EBIT)	(7) ln (EBITDA)	(8) ln (Earnings Per Share)
ln (AI Tech)	0.12**	0.25***	0.31***	0.229	0.20**	0.102	0.14*	0.073
	(0.05)	(0.08)	(0.11)	(0.18)	(0.10)	(0.11)	(0.08)	(0.15)
ln (Non-AI Tech)	0.053	-0.011	-0.22**	-0.037	-0.108	-0.093	-0.118	-0.147
	(0.05)	(0.09)	(0.11)	(0.22)	(0.10)	(0.11)	(0.08)	(0.20)
ln (Labor)	0.07***	0.19***	0.11***	0.24***	0.23***	0.11***	0.08***	0.087
	(0.02)	(0.03)	(0.04)	(0.09)	(0.03)	(0.04)	(0.03)	(0.06)
ln (Capital)	0.24***	0.53***	0.56***	0.59***	0.65***	0.59***	0.69***	-0.046
	(0.03)	(0.03)	(0.04)	(0.08)	(0.04)	(0.05)	(0.04)	(0.08)
ln (Int. Input)	0.60***	0.11***	0.14***	0.02	-0.09**	0.16***	0.15***	0.12**
	(0.03)	(0.03)	(0.04)	(0.07)	(0.04)	(0.04)	(0.04)	(0.06)
Firm Age	-0.00**	-0.00*	-0.001	0.00***	-0.00***	-0.001	-0.001	-0.001
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Constant	0.71**	0.375	0.692	0.103	3.58***	0.003	-0.19	1.151
	(0.28)	(0.46)	(0.62)	(1.11)	(0.55)	(0.61)	(0.47)	(1.46)
Observations	423.00	422.00	394.00	286.00	416.00	408.00	413.00	394.00
R-squared	0.931	0.752	0.599	0.483	0.622	0.592	0.771	0.038

Note: The model was run on 8 outcome variables for a filtered sample only including firms with one or more AI technologies. ln(AI Tech) is the natural log of the amount of AI technologies used in a company. Before running the model, a unit was added to ln(AI Tech) to ensure the logarithm is fully defined in the case when a firm has zero AI tech. Similarly, ln(Non-AI Tech) is the natural log of the non-AI technologies, calculated by subtracting AI tech from the number of total pieces of tech in a firm. This was not adjusted for the logarithm since there were no firms with zero non-AI tech. Observations fluctuations are due to missing or misreported financial data.
Robust standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1

Figure 2: *Summarized Results of Aggregate and Intensive Effects*

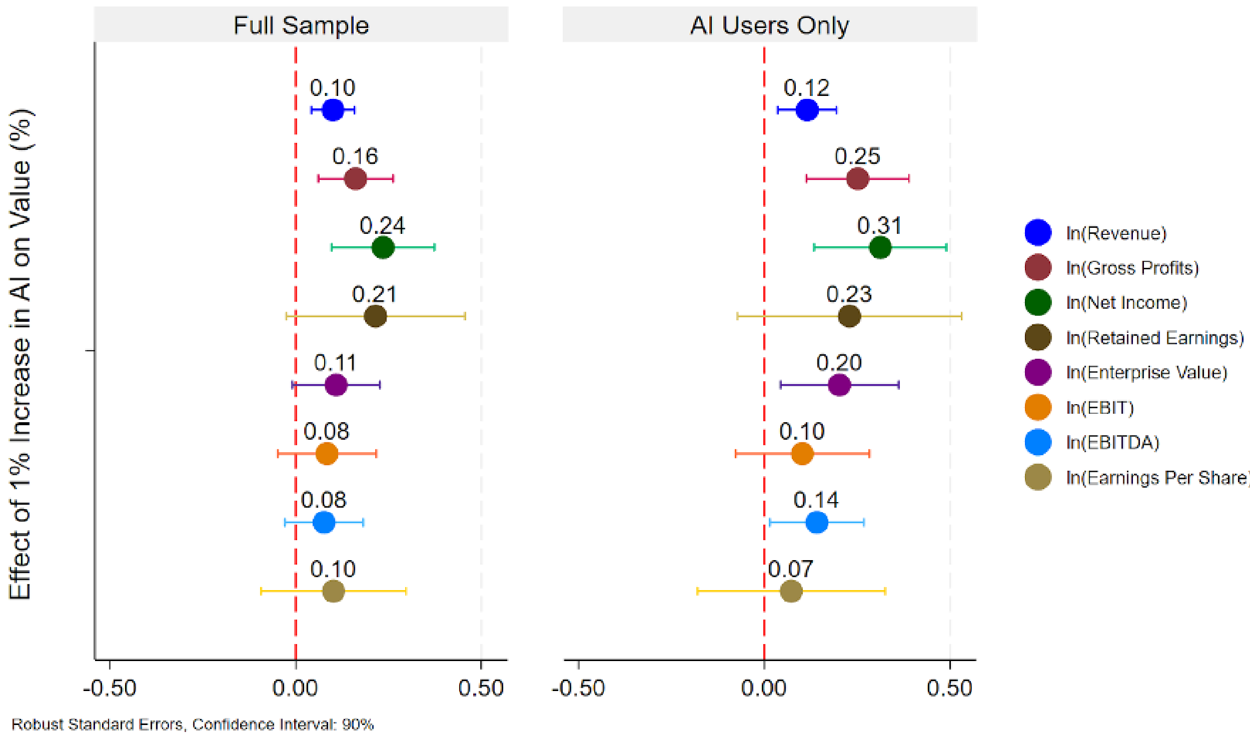


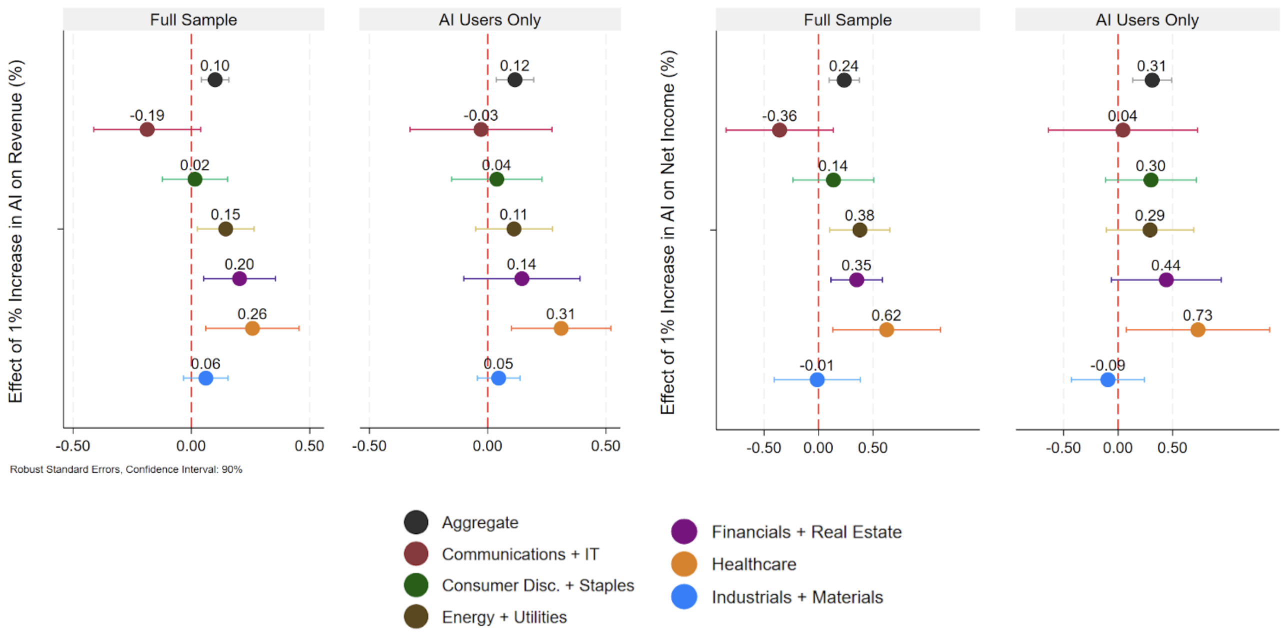
Table 3 shows all coefficients are positive, again identifying a positive correlation between AI technologies and value. Five significant coefficients provide statistical evidence for said trend and bring the average value increase for a 1% increase in AI adoption to 0.2%, or to a 20% increase in value for a 100% increase in AI adoption. R-squared and the other coefficients behave similarly to the aggregate results, confirming robustness. Since we observe a positive average effect of AI on AI-using firms, the model also satisfies our hypothesis that adding more AI technologies to firms that already use them brings a positive benefit.

When comparing the two sets of results, we must first notice that all effects, with the exception of Earnings Per Share, increase in magnitude when removing non-AI-using firms from the sample. This could indicate that the effect in the aggregate could be muted or not accurately estimated due to the large variability in the firms and their financial values. Particularly, the coefficients for Enterprise Value and EBITDA become significant in the AI-only sample, reinforcing the claim that the aggregate effects could be too noisy to be accurately estimated. Considering both aggregate and intensive results, we see a clear positive impact of AI technologies on business value that the model can quantify to 17 to 20% for a 100% AI adoption increase. These positive estimations are in line with the general literature and overall confirm the paper's hypothesis.

IV. Sector-Specific Results

To analyze the differences in AI benefits across industries, we apply our model separately for each of the six sector bins described in Table 8. Each sector received eight regressions, one for each outcome variable, for a sum of 48 regressions. This was repeated for the intensive margin, reaching 96 regressions. Multicollinearity was again not found through the VIF test. Detailed results for these are shown in Table 9 and Table 10, where each number represents the coefficient of interest in a single regression. Figure 3 illustrates the results for the Revenue and Net Income outcomes, which best represent the full set of coefficients. A full comparison of sector effects versus the aggregate is provided in Figure 5 and Figure 6. For these figures, it should be noted that the legend now represents sectors instead of outcome variables.

Figure 3: *Summarized Sector-Specific Effects on Revenue and Net Income*



These results reveal that AI impacts on business value are not homogeneous across sectors. Healthcare consistently shows positive and significant effects across six value metrics. Their average is 0.55% (0.64% in the AI-only sample), which is higher than the aggregate average. Financials + Real Estate shows significant effects in three value metrics in the full sample, averaging 0.25%. However, they become insignificant in the AI-only sample. Similarly, Energy + Utilities shows significant full-sample effects averaging 0.45% from six value metrics, which reduce to one value metric in the AI-only sample (with a maximal 1.1%). This could be due to these two sector pairs having a high amount of non-AI-using firms, which could have penalized the significance of their coefficients in the AI-only sample.

Communications + IT show a particularly interesting result, with a negative effect in the full sample from three value metrics averaging -0.65%. This counterintuitive result does not repeat in the AI-only sample and is the only outlier in the sector results. The remaining sector pairs showed no statistical significance. Overall, we find that the Healthcare, Energy, Utilities, Financial, and Real Estate sectors show sensitivity to AI adoption. We provide a deeper interpretation in the Results Discussion.

V. Further Robustness Checks

We replicate the aggregate and intensive regressions and add interaction terms between AI_i and select control variables, namely labor, capital, and firm age. Table 11 to Table 18 display the regression results.

We test the interaction with labor in two ways. First, we use a direct interaction term. We observe that our coefficient of interest becomes negative and the interaction term is positive. While almost no coefficients are statistically significant, this dynamic could imply that AI benefits scale with the number of employees in a firm. This could be connected to upskilling, in which employees can create more synergies when using advanced technologies thanks to training. A discussion could spark between this theory and the fear of automation pushing employers to replace human jobs, even though firms already seem to prefer reskilling their employees instead (Chui et al., 2023a).

Furthermore, we use labor interaction to test whether a firm being large has any effect on AI benefits. We take the average number of employees in the sample and create a binary variable equal to 1 for firms with above-average employee count. In this set of results, all coefficients of interest are positive and three value metrics remain robust and significant with an average effect of 0.18% (0.20% for the intensive margin). No interaction term is found to be significant. We can infer that being a large firm does not impact AI benefits.

Interaction with capital shows a more overwhelming set of results: the coefficient of interest is negative and significant for six value metrics (four in the intensive margin) and the interaction term is positive and significant for six (five in the intensive margin). Capital is therefore necessary for AI to benefit firms, and higher amounts of capital increase the effectiveness of AI in boosting the firm. Margins analysis was not conducted, but could provide additional insights into a possible minimum capital requirement for AI to become beneficial for a firm. This connection between AI technologies and capital is coherent with Arslan and Ozturan (2011) in that IT investments increase a company's performance if supported by complementary resources and if they are aligned with the company's core competencies.

Lastly, we look at firm age interaction to explore how it affects the strength of AI benefits. Arslan and Ozturan (2011) suggest that more established firms could be stronger and more mature in their internal processes while also being more stable in performance. In the results, coefficients for two value metrics remain robust with an average effect of 0.23%, as well as four in the intensive margin with an average effect of 0.25%. Only the interaction coefficient for retained earnings is found to be non-zero (positive) and statistically significant, but still remains close to zero. We conclude that firm age has no effect on AI benefits.

VI. Results Discussion

Overall, the results match our hypothesis that AI tends to positively impact firms' business value. In the full sample, there are clear differences in performance between firms that use AI and those that do not. This could imply a strategic advantage for firms that adopt AI before their competitors, as the latter would fall behind. As Nafizah et al. (2023) find for micro-enterprises, a high-cap firm could similarly benefit from a period of first-mover advantage through an increased capability to introduce innovation outcomes. The costs of training a competitive AI model have sharply increased in recent years (Maslej et al., 2024), implying that a firm implementing such a technology would make it hard for its competitors to match.

However, Nguyen and Hambur (2023) find that early adopters of general-purpose technologies (including AI) actually experience reduced profitability, and that this phenomenon is observed less in more recent cases. This could hint that AI technology may have become easier and less expensive to adopt over time, pointing to a theory that first-mover advantages have already depleted in recent years. We leave this insight open to further contributions, proposing it could be explored through an event study using data on the date that firms adopted their AI technologies.

Our sector analysis finds the Healthcare, Energy, Utilities, Financial, and Real Estate sectors to be sensitive to AI benefits. The first is not surprising, as efforts to apply AI to Healthcare have been high since the 1970s given its potential in areas including patient care and healthcare provider administration (Davenport and Kalakota, 2019). Tools such as neural networks have shown success in disease diagnosis and image recognition, demonstrating performance comparable to that of expert medical practitioners (Shen et al., 2019). AI's increased capabilities, accuracy, adoption, and government approval in medicine contributed to the advancement of the field in recent years (Maslej et al., 2024), which can justify the sector's sensitivity in our results.

As for the Energy and Utilities sectors, some AI applications are currently being explored through capabilities such as RD, data management, and energy-saving optimization (Wang et al., 2024; Tiwari, 2023). Similarly, AI in Finance and Real Estate is being explored in areas such as process automation, data analytics, predictive systems, and client personalization (Bahoo et al., 2024; Antão et al., 2024). However, these are still at an early stage and research is still largely lacking, especially concerning performance and accuracy analysis of AI solutions (Antão et al., 2024). This relative novelty of AI in the Energy, Utilities, Financial, and Real Estate sectors could justify the lack of robustness for those sector effects when reducing the sample to AI-using firms.

The negative sensitivity of the Communications + IT pair in the full sample is quite intriguing. The financial outcomes of such companies should intuitively be connected to the overall success of AI, since IT firms tend to be those most involved in the provision and even creation of such technologies. In our sample, firms in this pair have the highest average AI adoption, and many technologies used by other companies have been provided by members of this pair (such as IBM, Google, and Microsoft).

A possible effect could be the diminishing marginal returns of AI, in which we would see a firm's utility gain from a new AI technology reduce with each added technology. Perhaps the improvement costs of AI tools increase exponentially, as argued by Thompson et al. (2021) who claim that halving the error rate of a deep learning model would require more than 500 times the computational resources including processors and running time. Perhaps the very benefit gained from AI becomes less impactful as more technologies are acquired, possibly due to those technologies overlapping in function and therefore not providing unique capabilities to the firm. Either way, our results point to the need for a more granular exploration of the Communications and IT industries given their central role in the diffusion and advancement of AI technologies.

Lastly, there is a discussion to be made on the statistical significance of our results. While we consider the effects of AI technologies on each outcome variable and each sector as separate, this could instead be done through multiple hypothesis testing to ensure no hypothesis is falsely rejected (Higdon, 2013). The risk lies in the use of per-comparison error rates (which consider the probability of wrongly rejecting a single null hypothesis) as opposed to the usually higher family-wise error rate (which considers the probability of falsely rejecting a hypothesis at least once in a group of related tests). A simple but conservative fix would be to apply the Bonferroni correction to control the family-wise error rate (Haynes, 2013), an endeavor that we leave up to future research.

V. Conclusion & Extensions

We present one of the first non-survey datasets and methods for the quantification of AI benefits for firms. We create a Cobb-Douglas OLS model inspired by available literature on AI and innovation in businesses. Our methodology attempts to address simultaneity and omitted variable bias by collecting relevant insights from past literature on control variables for factors of production and firm-specific characteristics. Access to a database of technologies used by S&P 500 firms allowed the direct application of our model, which found results coherent with the overall positive perception of AI in the professional world.

We provide a first quantification of the average monetary benefits of AI technologies in those firms amounting to 17% for a 100% increase in AI adoption. For firms that already use AI, this is found to be 20%. We also attempt a sector-specific investigation, which finds Healthcare, Energy, Utilities, Financials, and Real Estate to be sensitive to AI benefits at varying levels. The sector outliers Communications + IT and the results of our interaction robustness checks highlight areas for further exploration including the marginal returns of AI and the implications of upskilling.

Our findings are relevant for many key players in the economy. Firms and investors equipped with quantified predictions of AI benefits can better forecast returns and risks before dedicating time and resources to acquire or invest in said technology. Additionally, specific industry predictions can help researchers and market players navigate the rates at which different sectors innovate and adapt to AI. Policymakers aiming to support the use and adoption of AI may use such predictions to better estimate the effects of AI on an economy or market, as well as on critical sectors such as Healthcare and Energy.

The literature gives us a word of caution. Predictions of the likely effects of AI may only truly represent the current stage of the technology's diffusion, exposing research and methods to quickly become obsolete due to the rapid pace of AI innovation (Rammer et al., 2022). Much like the very nature of AI as a technology, its study is a constantly growing movement. Hence, while we provide a baseline method and a descriptive set of results, the main goal of this paper is to stimulate additional contributions and urge for a structured approach to research on the subject.

Continuing and expanding our investigation periodically would unlock the use of lagged values, helpful for mitigating the effects of simultaneity and shedding more light on causality. Including a time dimension is particularly important to capture the fast-paced evolution of AI technologies and adoption trends that we only study superficially in this paper. Additionally, other academics may also want to specialize or reapply our model to focused contexts such as specific sectors, geographies, or type of AI technology.

Aside from the aforementioned extensions stemming from our results and robustness checks, we propose further exploration on the topic of SMEs, an often understudied yet critical portion of the global economy. If data is made available, research on other stock exchanges and firm samples would yield insights into the effects of AI in other geographies, which could reveal if differences in how governments promote AI adoption impact how beneficial the technology is for different firms. An investigation could also be done to dissect these AI benefits into its possible channels, such as revenue generation and cost reduction, to further explore the most effective conditions for AI to boost businesses. Lastly, a more granular view of AI in firms could be gained by examining the benefits of each type of AI technology, such as reactive machine versus limited memory AI (Hassani et al., 2020).

In conclusion, this paper serves as a first step towards understanding the transformative potential of AI for businesses, paving the way for further exploration in this emerging domain. We hope this paper can act as an inspiration and a starting point for future contributions, fostering a richer understanding of AI's profound benefits to businesses worldwide.

References

Acemoglu, Daron, and David Autor. 2011. "Skills, Tasks and Technologies: Implications for Employment and Earnings*.” In *Handbook of Labor Economics*, edited by David Card and Orley Ashenfelter, 4:1043–1171. Elsevier. https://doi.org/10.1016/S0169-7218(11)02410-5.

Aghion, Philippe, Benjamin F. Jones, and Charles I. Jones. 2018. “Artificial Intelligence and Economic Growth.” In *The Economics of Artificial Intelligence: An Agenda*, 237–82. University of Chicago Press. https://www.nber.org/books-and-chapters/economics-artificial-intelligence-agenda/artificial-intelligence-and-economic-growth.

Agrawal, Ajay, Joshua Gans, and Avi Goldfarb. 2019. “Economic Policy for Artificial Intelligence.” In *Innovation Policy and the Economy* 19 (January): 139–59. https://doi.org/10.1086/699935.

Antão, João, Ricardo Ribeiro, and Rúben Pereira. 2024. “Applications, Opportunities and Challenges of AI in the Real Estate Sector.” https://doi.org/10.21203/rs.3.rs-4001575/v1.

Arslan, Birgul, and Meltem Ozturan. 2011. “The Path to Information Technology Business Value: Case of Turkey.” *Technology and Investment* 2 (1): 52–63. https://doi.org/10.4236/ti.2011.21007.

Bahoo, Salman, Marco Cucculelli, Xhoana Goga, and Jasmine Mondolo. 2024. “Artificial Intelligence in Finance: A Comprehensive Review through Bibliometric and Content Analysis.” *SN Business & Economics* 4 (2): 23. https://doi.org/10.1007/s43546-023-00618-x.

Beers, Brian. 2023. “Why Do Investors Use the S&P 500 as a Benchmark?” *Investopedia*. August 30, 2023. https://www.investopedia.com/ask/answers/041315/what-are-pros-and-cons-using-sp-500-benchmark.asp.

Bloom, Nicholas, Charles I. Jones, John Van Reenen, and Michael Webb. 2020. “Are Ideas Getting Harder to Find?” *American Economic Review* 110 (4): 1104–44. https://doi.org/10.1257/aer.20180338.

Brynjolfsson, Erik, Daniel Rock, and Chad Syverson. 2017. “Artificial Intelligence and the Modern Productivity Paradox: A Clash of Expectations and Statistics.” Working Paper. Working Paper Series. *National Bureau of Economic Research*. https://doi.org/10.3386/w24001.

Cambon, Alexia, Brent Hecht, Ben Edelman, Donald Ngwe, Sonia Jaffe, Amy Heger, Sida Peng, et al. 2023. “Early LLM-Based Tools for Enterprise Information Workers Likely Provide Meaningful Boosts to Productivity.” *Microsoft*.

Chui, Michael, Bryce Hall, Alex Singla, Alexander Sukharevsky, and Helen Mayhew. 2022. “The State of AI in 2022—and a Half Decade in Review | McKinsey.” *McKinsey, Quantum Black*. Accessed December 5, 2023. https://www.mckinsey.com/capabilities/quantumblack/our-insights/the-state-of-ai-in-2022-and-a-half-decade-in-review.

Chui, Michael, Bryce Hall, Alex Singla, Alexander Sukharevsky, and Lareina Yee. 2023a. “The State of AI in 2023: Generative AI’s Breakout Year.” *McKinsey, Quantum Black*. Accessed December 5, 2023. https://www.mckinsey.com/capabilities/quantumblack/our-insights/the-state-of-ai-in-2023-generative-ais-breakout-year?gclid=EAIaIQobChMI49W31vf4ggMVMIuDBx1tiAPNEAAYASAAEgI88PD_BwE.

Chui, Michael, Eric Hazan, Roger Roberts, Alex Singla, Kate Smaje, Alexander Sukharevsky, Lareina Yee, and Rodney Zemmel. 2023b. “The Economic Potential of Generative AI: The next Productivity Frontier.” *McKinsey Digital*. June 14, 2023. https://www.mckinsey.com/capabilities/mckinsey-digital/our-insights/the-economic-potential-of-generative-ai-the-next-productivity-frontier.

Coad, Alex, Agusti Segarra Blasco, and Mercedes Teruel. 2013. “Innovation and Firm Growth: Does Firm Age Play a Role?” *SSRN Scholarly Paper*. Rochester, NY. https://doi.org/10.2139/ssrn.2276414.

Cockburn, Iain M., Rebecca Henderson, and Scott Stern. 2018. “The Impact of Artificial Intelligence on Innovation: An Exploratory Analysis.” In *The Economics of Artificial Intelligence: An Agenda*, 115–46. University of Chicago Press. https://www.nber.org/books-and-chapters/economics-artificial-intelligence-agenda/impact-artificial-intelligence-innovation-exploratory-analysis.

Czarnitzki, Dirk, Gastón P. Fernández, and Christian Rammer. 2022. “Artificial Intelligence and Firm-Level Productivity.” Working Paper 22–005. *ZEW Discussion Papers*. https://www.econstor.eu/handle/10419/250389.

Davenport, Thomas, and Ravi Kalakota. 2019. “The Potential for Artificial Intelligence in Healthcare.” *Future Healthcare Journal* 6 (2): 94–98. https://doi.org/10.7861/futurehosp.6-2-94.

Dewald, William G., Jerry G. Thursby, and Richard G. Anderson. 1986. “Replication in Empirical Economics: The Journal of Money, Credit and Banking Project.” *The American Economic Review* 76 (4): 587–603.

Downing, Dixie, and Fernando Garcia. 2021. "Demographic Makeup of SMEs in the United States and United Kingdom." *United States International Trade Commission*, July. https://www.usitc.gov/publications/332/executive_briefings/ebot_demographic_makeup_of_smes_in_the_united_states_and_united_kingdom.pdf.

Dun & Bradstreet. 2022. *D&B Hoovers Technology Insights*. https://www.youtube.com/watch?v=qT7i-XXg2j0.

Enholm, Ida Merete, Emmanouil Papagiannidis, Patrick Mikalef, and John Krogstie. 2022. "Artificial Intelligence and Business Value: A Literature Review." *Information Systems Frontiers* 24 (5): 1709–34. https://doi.org/10.1007/s10796-021-10186-w.

"Google Trends." 2023. *Google Trends*. Accessed December 2, 2023. https://trends.google.com/trends/explore?date=2021-02-02%202023-12-02&q=%2Fm%2F0mkz&hl=en-GB.ù

Gordon, Robert J. 2018. "Why Has Economic Growth Slowed When Innovation Appears to Be Accelerating?" Working Paper. Working Paper Series. *National Bureau of Economic Research*. https://doi.org/10.3386/w24554.

Hassani, Hossein, Emmanuel Sirimal Silva, Stephane Unger, Maedeh TajMazinani, and Stephen Mac Feely. 2020. "Artificial Intelligence (AI) or Intelligence Augmentation (IA): What Is the Future?" *AI* 1 (2): 143–55. https://doi.org/10.3390/ai1020008.

Haynes, Winston. 2013. "Bonferroni Correction." In *Encyclopedia of Systems Biology*, edited by Werner Dubitzky, Olaf Wolkenhauer, Kwang-Hyun Cho, and Hiroki Yokota, 154–154. New York, NY: Springer. https://doi.org/10.1007/978-1-4419-9863-7_1213.

Higdon, Roger. 2013. "Multiple Hypothesis Testing." In *Encyclopedia of Systems Biology*, edited by Werner Dubitzky, Olaf Wolkenhauer, Kwang-Hyun Cho, and Hiroki Yokota, 1468–69. New York, NY: Springer. https://doi.org/10.1007/978-1-4419-9863-7_1211.

Jann, Ben. 2014. "A New Command for Plotting Regression Coefficients and Other Estimates." University of Bern, June.

Kane, John V. 2024. "Making Regression Coefficient Plots in Stata." *The Stata Gallery* (blog). March 1, 2024. https://medium.com/the-stata-gallery/making-regression-coefficient-plots-in-stata-7b100feac0cb.

Maslej, Nestor, Loredana Fattorini, Raymond Perrault, and Vanessa Parli. 2023. "AI Index Report 2023 – Artificial Intelligence Index." Institute for Human-Centered AI, Stanford University. https://aiindex.stanford.edu/ai-index-report-2023/.

Maslej, Nestor, Loredana Fattorini, Raymond Perrault, and Vanessa Parli. 2024. "AI Index Report 2024 – Artificial Intelligence Index." Institute for Human-Centered AI, Stanford University. https://aiindex.stanford.edu/report/.

Nafizah, Ully Y., Stephen Roper, and Kevin Mole. 2023. "Estimating the Innovation Benefits of First-Mover and Second-Mover Strategies When Micro-Businesses Adopt Artificial Intelligence and Machine Learning." *Small Business Economics* 62 (1): 411–34. https://doi.org/10.1007/s11187-023-00779-x.

Nguyen, Kim, and Jonathan Hambur. 2023. "RDP 2023-10: Adoption of Emerging Digital General-Purpose Technologies: Determinants and Effects." *Research Discussion Papers*, no. June. https://doi.org/10/full.html.

Peters, Bettina, and Christian Rammer. 2023. "Innovation Panel Surveys in Germany: The Mannheim Innovation Panel." In *Handbook of Innovation Indicators and Measurement*, 54–87. Edward Elgar Publishing. https://www.elgaronline.com/edcollchap/book/9781800883024/book-part-9781800883024-14.xml.

Rahwan, Talal, and Yasir Zaki. 2023. "Perception, Performance, and Detectability of Conversational Artificial Intelligence across 32 University Courses." *Scientific Reports* 13 (1): 12187. https://doi.org/10.1038/s41598-023-38964-3.

Rammer, Christian, Gastón P. Fernández, and Dirk Czarnitzki. 2022. "Artificial Intelligence and Industrial Innovation: Evidence from German Firm-Level Data." *Research Policy* 51 (7): 104555. https://doi.org/10.1016/j.respol.2022.104555.

Ravichandran, T., and Chalermsak Lertwongsatien. 2005. "Effect of Information Systems Resources and Capabilities on Firm Performance: A Resource-Based Perspective." *Journal of Management Information Systems* 21 (March): 237–76.

Seamans, Robert, and Manav Raj. 2018. "AI, Labor, Productivity and the Need for Firm-Level Data." Working Paper. *Working Paper Series*. National Bureau of Economic Research. https://doi.org/10.3386/w24239.

Shen, Jiayi, Casper J. P. Zhang, Bangsheng Jiang, Jiebin Chen, Jian Song, Zherui Liu, Zonglin He, Sum Yi

Wong, Po-Han Fang, and Wai-Kit Ming. 2019. "Artificial Intelligence Versus Clinicians in Disease Diagnosis: Systematic Review." *JMIR Medical Informatics* 7 (3): e10010. https://doi.org/10.2196/10010.

Solow, Robert M. 1987. "We'd Better Watch Out." *New York Times*, July 12, 1987.

Thompson, Neil C., Kristjan Greenewald, Keeheon Lee, and Gabriel F. Manso. 2021. "Deep Learning's Diminishing Returns." *IEEE Spectrum*, September 24, 2021. https://spectrum.ieee.org/deep-learning-computational-cost.

Tiwari, Seemant. 2023. "Artificial Intelligence (AI) in the Sustainable Energy Sector." *Engineering Proceedings* 37 (1): 11. https://doi.org/10.3390/ECP2023-14609.

Tudorache, Dragos. 2023. "Artificial Intelligence Act: Deal on Comprehensive Rules for Trustworthy AI." *European Parliament*. December 9, 2023. https://www.europarl.europa.eu/news/en/press-room/20231206IPR15699/artificial-intelligence-act-deal-on-comprehensive-rules-for-trustworthy-ai.

Wang, Bo, Jianda Wang, Kangyin Dong, and Rabindra Nepal. 2024. "How Does Artificial Intelligence Affect High-Quality Energy Development? Achieving a Clean Energy Transition Society." *Energy Policy* 186 (March): 114010. https://doi.org/10.1016/j.enpol.2024.114010.

Wooldridge, Jeffrey M. 2008. *Introductory Econometrics: A Modern Approach*. Cengage Learning.

Zeira, Joseph. 1998. "Workers, Machines, and Economic Growth." *The Quarterly Journal of Economics* 113 (4): 1091–1117. http://www.jstor.org/stable/2586975.

VI. Appendix

I. Appendix A - Summary Statistics & Correlations

Table 4: *Summary Statistics for AI-Related Variables*

Variable Name	Unit	Count	Mean	St. Dev	Min	Max
AI Tech	Individual software/hardware	489	3.69	2.72	0.00	14.00
Non-AI Tech	Individual software/hardware	489	995.78	580.35	3.00	4007.00

Table 5: *Summary Statistics for Financial Value Metrics*

Variable Name	Unit	Count	Mean	St. Dev	Min	Max
Revenues	$USD mln	489	32512.80	64982.08	752.55	648125.00
Gross Profits	$USD mln	489	12235.25	24495.33	-2344.00	270046.00
Net Income	$USD mln	489	3490.75	9031.86	-24271.00	100913.00
Retained Earnings	$USD mln	489	14592.83	44549.04	-26549.00	569776.00
Enterprise Value	$USD mln	462	101207.90	253570.80	4242.48	3023281.00
EBIT	$USD mln	462	4683.33	10785.55	-6391.00	118658.00
EBITDA	$USD mln	462	6285.66	13169.40	-2166.00	130109.00
EPS	$USD	489	115.88	2384.22	-41.00	52728.22

Table 6: *Summary Statistics for Control Variables*

Variable Name	Unit	Count	Mean	St. Dev	Min	Max
Employees	# of employees	489	58004.56	140597.40	23.00	2100000.00
Capital	$USD mln	489	34602.32	65954.88	0.00	759000.00
COGS	$USD mln	489	19848.87	46073.31	0.00	490142.00
Year Founded	Year	489	1945.70	51.70	1774.00	2022.00

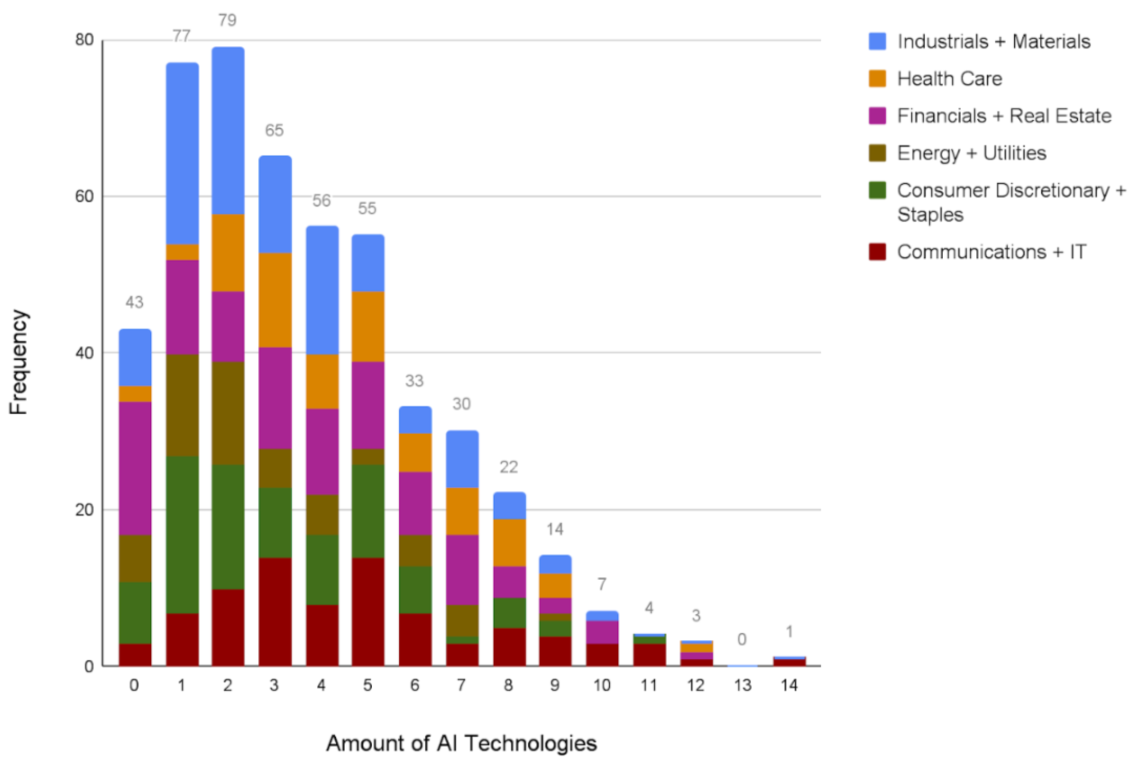
Table 7: *Sector Composition and AI Summary*

Sector	Frequency	Percent	Mean AI	Min AI	Max AI
Communication Services	19	3.89	6.26	3	11
Consumer Discretionary	51	10.43	3.49	0	11
Consumer Staples	37	7.57	2.73	0	9
Energy	23	4.7	3.17	0	7
Financials	71	14.52	4.69	0	12
Health Care	63	12.88	4.6	0	12
Industrials	75	15.34	3.39	0	10
Information Technology	64	13.09	4.38	0	14
Materials	27	5.52	2.41	0	7
Real Estate	29	5.93	1.31	0	4
Utilities	30	6.13	2.4	0	9
Total	489	100			

Table 8: *Sector Composition and AI Summary After Pairing*

Sector	Frequency	Percent	Mean AI	Min AI	Max AI
Communications + IT	83	16.97	4.81	0	14
Consumer Discretionary + Staples	88	18	3.17	0	11
Energy + Utilities	53	10.84	2.74	0	9
Financials + Real Estate	100	20.45	3.71	0	12
Health Care	63	12.88	4.6	0	12
Industrials + Materials	102	20.86	3.13	0	10
Total	489	100			

Figure 4: *Distribution of AI Technologies by Sector Pair*



II. Appendix B - Full Results of Sector Analysis

Table 9: *Full Sector-Specific Results*

Sector Pair	(1) ln (Revenue)	(2) ln (Gross Profits)	(3) ln (Net Earnings)	(4) ln (Retained Earnings)	(5) ln (Enterprise Value)	(6) ln (EBIT)	(7) ln (EBITDA)	(8) ln (Earnings Per Share)
Communications + IT	-0.187	-0.386*	-0.357	-0.684	-0.411	-0.942**	-0.621**	-0.326
	(0.136)	(0.216)	(0.295)	(0.436)	(0.326)	(0.450)	(0.275)	(0.297)
Consumer Disc. + Staples	0.015	0.018	0.136	-0.069	0.028	0.087	0.066	-0.100
	(0.083)	(0.161)	(0.223)	(0.307)	(0.184)	(0.197)	(0.144)	(0.260)
Energy + Utilities	0.145**	0.416**	0.379**	1.229***	0.029	0.276**	0.226*	0.073
	(0.071)	(0.201)	(0.164)	(0.374)	(0.064)	(0.134)	(0.122)	(0.222)
Financials + Real Estate	0.204**	0.152	0.350**	0.487	0.192**	0.193	0.149	0.107
	(0.091)	(0.109)	(0.142)	(0.293)	(0.094)	(0.149)	(0.098)	(0.229)
Health Care	0.259**	0.392**	0.625**	-0.242	0.895***	0.641***	0.477**	-0.310
	(0.118)	(0.194)	(0.295)	(0.430)	(0.245)	(0.209)	(0.213)	(0.380)
Industrials + Materials	0.061	0.070	-0.012	-0.068	-0.116	-0.120	-0.082	0.190
	(0.057)	(0.113)	(0.237)	(0.339)	(0.140)	(0.202)	(0.148)	(0.289)

Note: The model was run on 8 outcome variables for all firms in each of the 6 sector pairs, for a total of 48 regressions. Each coefficient in this table represents the effect of interest *ln(AI Tech)* for one of those sector regressions. Therefore, this table represents 48 separate regressions.
Robust standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1

Table 10: *Full Sector-Specific Results (AI Users Only)*

Sector Pair	(1) ln (Revenue)	(2) ln (Gross Profits)	(3) ln (Net Earnings)	(4) ln (Retained Earnings)	(5) ln (Enterprise Value)	(6) ln (EBIT)	(7) ln (EBITDA)	(8) ln (Earnings Per Share)
Communications + IT	-0.028	-0.074	0.045	-0.644	-0.038	-0.803	-0.349	-0.021
	(0.180)	(0.291)	(0.410)	(0.662)	(0.388)	(0.727)	(0.311)	(0.456)
Consumer Disc. + Staples	0.039	0.135	0.302	0.279	0.162	0.148	0.179	-0.161
	(0.115)	(0.207)	(0.250)	(0.403)	(0.248)	(0.201)	(0.165)	(0.266)
Energy + Utilities	0.111	0.384	0.293	1.099***	-0.002	0.215	0.175	0.248
	(0.096)	(0.280)	(0.238)	(0.385)	(0.094)	(0.173)	(0.162)	(0.312)
Financials + Real Estate	0.144	0.113	0.442	0.555	0.283	0.233	0.297	0.401
	(0.147)	(0.186)	(0.301)	(0.590)	(0.220)	(0.296)	(0.182)	(0.523)
Health Care	0.310**	0.576***	0.733*	-0.342	0.869***	0.747***	0.577**	-0.354
	(0.126)	(0.198)	(0.393)	(0.592)	(0.317)	(0.249)	(0.278)	(0.523)
Industrials + Materials	0.046	0.046	-0.094	-0.074	-0.140	-0.227	-0.124	0.187
	(0.054)	(0.113)	(0.202)	(0.324)	(0.148)	(0.183)	(0.139)	(0.275)

Note: The model was run on 8 outcome variables for AI-using firms in each of the 6 sector pairs, for a total of 48 regressions. Each coefficient in this table represents the effect of interest *ln(AI Tech)* for one of those sector regressions. Therefore, this table represents 48 separate regressions.
Robust standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1

Figure 5: *Full Comparison of Sector Effects Versus Aggregate*

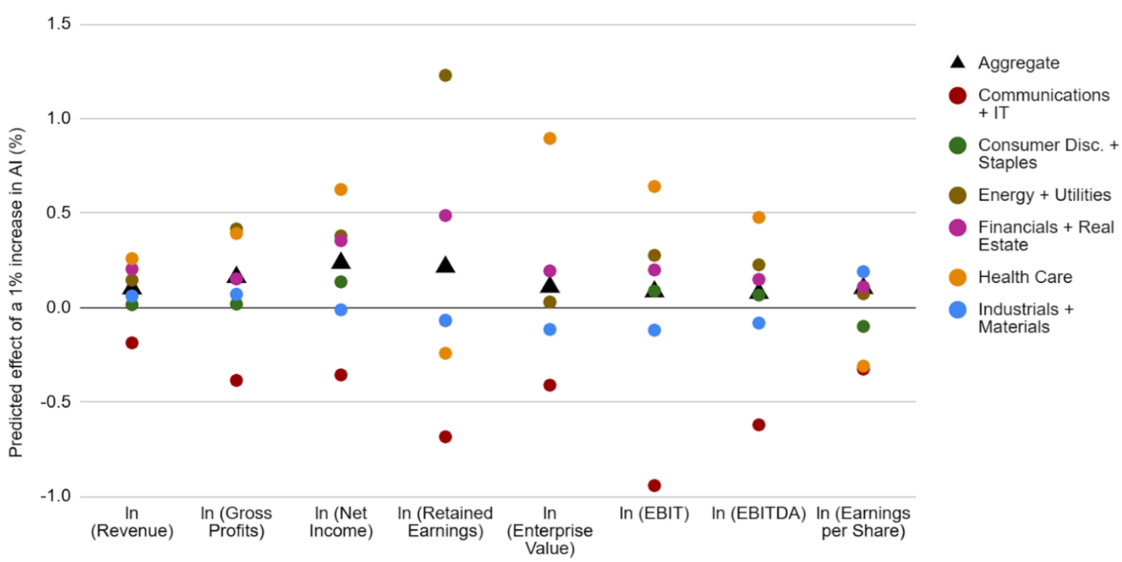
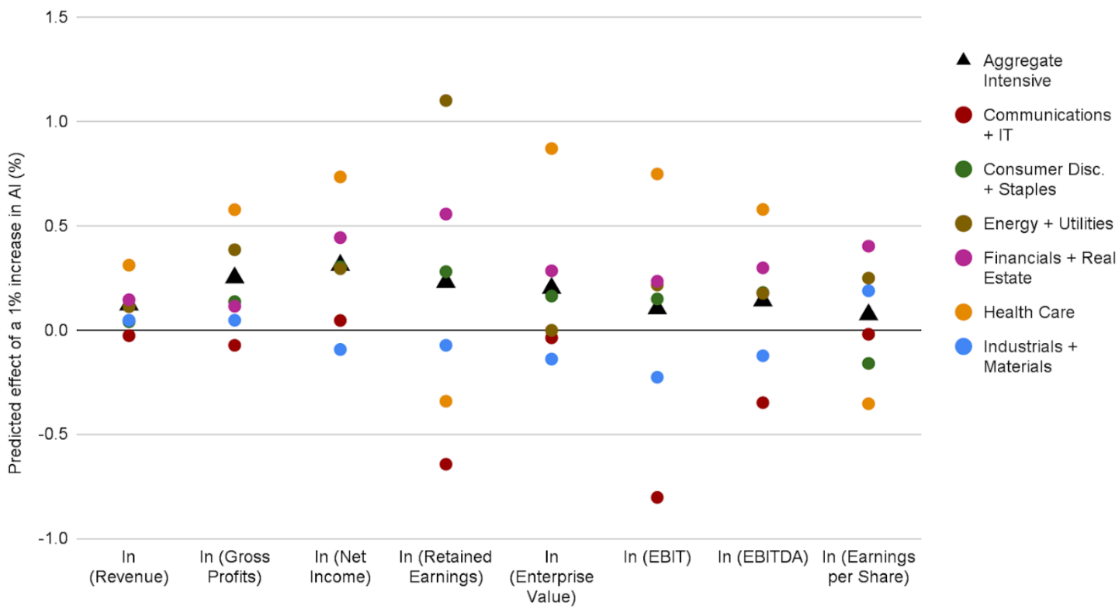


Figure 6: *Full Comparison of Sector Effects Versus Aggregate (AI Users Only)*



III. Appendix C - Robustness Checks

Table 11: *Robustness Check with Labor Interaction*

	(1) ln (Revenue)	(2) ln (Gross Profits)	(3) ln (Net Earnings)	(4) ln (Retained Earnings)	(5) ln (Enterprise Value)	(6) ln (EBIT)	(7) ln (EBITDA)	(8) ln (Earnings Per Share)
ln (AI Tech)	-0.41	-0.30	-0.19	-0.45	-0.40	-0.40	-0.570*	0.06
	(0.31)	(0.31)	(0.46)	(0.59)	(0.32)	(0.40)	(0.31)	(0.56)
ln (Labor)	-0.01	0.122**	0.05	0.14	0.157***	0.03	-0.01	0.10
	(0.06)	(0.05)	(0.08)	(0.12)	(0.05)	(0.07)	(0.05)	(0.08)
ln (AI Tech) x ln (Labor)	0.051*	0.05	0.04	0.07	0.05	0.05	0.065**	0.01
	(0.03)	(0.03)	(0.05)	(0.06)	(0.03)	(0.04)	(0.03)	(0.05)
ln (Non-AI Tech)	0.06	0.05	-0.158**	-0.07	0.01	-0.06	-0.08	-0.23
	(0.04)	(0.06)	(0.07)	(0.15)	(0.07)	(0.07)	(0.07)	(0.15)
ln (Capital)	0.235***	0.507***	0.511***	0.526***	0.606***	0.545***	0.642***	-0.08
	(0.03)	(0.04)	(0.05)	(0.08)	(0.05)	(0.05)	(0.04)	(0.07)
ln (Int. Input)	0.592***	0.116***	0.155***	0.07	-0.093**	0.176***	0.163***	0.132**
	(0.03)	(0.03)	(0.04)	(0.07)	(0.04)	(0.04)	(0.03)	(0.05)
Firm Age	-0.001*	0.00	0.00	0.004***	-0.002**	0.00	0.00	0.00
	0.00	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Constant	1.584***	0.92	1.28	1.64	3.998***	0.86	0.84	1.705*
	(0.52)	(0.58)	(0.85)	(1.22)	(0.68)	(0.77)	(0.67)	(1.01)
Observations	466.00	464.00	434.00	311.00	459.00	450.00	454.00	434.00
R-squared	0.93	0.75	0.58	0.46	0.62	0.59	0.76	0.05

Note: The model was run on 8 outcome variables for the full dataset of firms.
Robust standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1

Table 12: *Robustness Check with Labor Interaction (AI Users Only)*

	(1) ln (Revenue)	(2) ln (Gross Profits)	(3) ln (Net Earnings)	(4) ln (Retained Earnings)	(5) ln (Enterprise Value)	(6) ln (EBIT)	(7) ln (EBITDA)	(8) ln (Earnings Per Share)
ln (AI Tech)	-0.13	-0.29	-0.23	-0.21	-0.51	-0.32	-0.56	-0.09
	(0.25)	(0.40)	(0.50)	(0.85)	(0.44)	(0.49)	(0.38)	(1.11)
ln (Labor)	0.04	0.11	0.03	0.17	0.123*	0.04	-0.02	0.06
	(0.04)	(0.07)	(0.08)	(0.16)	(0.07)	(0.08)	(0.07)	(0.16)
ln (AI Tech) x ln (Labor)	0.02	0.05	0.05	0.04	0.07	0.04	0.068*	0.02
	(0.02)	(0.04)	(0.05)	(0.08)	(0.04)	(0.05)	(0.04)	(0.10)
ln (Non-AI Tech)	0.06	0.00	-0.204*	-0.03	-0.09	-0.08	-0.10	-0.14
	(0.05)	(0.09)	(0.11)	(0.22)	(0.10)	(0.10)	(0.08)	(0.21)
ln (Capital)	0.240***	0.523***	0.551***	0.589***	0.634***	0.585***	0.676***	-0.05
	(0.03)	(0.03)	(0.04)	(0.08)	(0.05)	(0.05)	(0.04)	(0.07)
ln (Int. Input)	0.597***	0.113***	0.138***	0.02	-0.086**	0.157***	0.151***	0.117**
	(0.03)	(0.03)	(0.04)	(0.07)	(0.04)	(0.04)	(0.04)	(0.06)
Firm Age	-0.001**	-0.001*	0.00	0.004***	-0.002***	0.00	0.00	0.00
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Constant	1.073**	1.16	1.48	0.75	4.633***	0.62	0.84	1.39
	(0.50)	(0.72)	(0.98)	(1.73)	(0.87)	(1.01)	(0.79)	(1.44)
Observations	423.00	422.00	394.00	286.00	416.00	408.00	413.00	394.00
R-squared	0.93	0.75	0.60	0.48	0.62	0.59	0.77	0.04

Note: The model was run on 8 outcome variables for a filtered sample only including firms with one or more AI technologies.
Robust standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1

Table 13: *Robustness Check with Labor Dummy Interaction*

	(1) ln (Revenue)	(2) ln (Gross Profits)	(3) ln (Net Earnings)	(4) ln (Retained Earnings)	(5) ln (Enterprise Value)	(6) ln (EBIT)	(7) ln (EBITDA)	(8) ln (Earnings Per Share)
ln (AI Tech)	0.109***	0.177***	0.240***	0.17	0.12	0.09	0.05	0.16
	(0.04)	(0.07)	(0.09)	(0.17)	(0.07)	(0.08)	(0.07)	(0.14)
Big firm	0.231**	0.520**	0.25	-0.07	0.484*	0.27	0.08	0.63
	(0.11)	(0.20)	(0.29)	(0.47)	(0.29)	(0.28)	(0.20)	(0.43)
ln (AI Tech) x Big firm	-0.05	-0.09	-0.03	0.16	-0.07	-0.05	0.08	-0.28
	(0.06)	(0.12)	(0.17)	(0.26)	(0.16)	(0.17)	(0.12)	(0.25)
ln (Non-AI Tech)	0.073**	0.132**	-0.11	0.06	0.121**	-0.03	-0.04	-0.18
	(0.04)	(0.05)	(0.07)	(0.16)	(0.06)	(0.06)	(0.07)	(0.15)
ln (Capital)	0.241***	0.493***	0.508***	0.514***	0.584***	0.544***	0.643***	-0.08
	(0.03)	(0.03)	(0.05)	(0.08)	(0.04)	(0.05)	(0.04)	(0.07)
ln (Int. Input)	0.607***	0.178***	0.189***	0.171***	-0.01	0.206***	0.180***	0.169***
	(0.03)	(0.03)	(0.03)	(0.07)	(0.06)	(0.04)	(0.03)	(0.04)
Firm Age	-0.001**	0.00	0.00	0.004***	-0.002***	0.00	0.00	0.00
	0.00	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Constant	1.208***	1.095***	1.174**	1.35	4.187***	0.61	0.38	1.93
	(0.25)	(0.39)	(0.55)	(1.07)	(0.48)	(0.53)	(0.49)	(1.18)
Observations	466.00	464.00	434.00	311.00	459.00	450.00	454.00	434.00
R-squared	0.93	0.74	0.58	0.45	0.59	0.58	0.76	0.05

Note: The model was run on 8 outcome variables for the full dataset of firms.
Robust standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1

Table 14: *Robustness Check with Labor Dummy Interaction (AI Users Only)*

	(1) ln (Revenue)	(2) ln (Gross Profits)	(3) ln (Net Earnings)	(4) ln (Retained Earnings)	(5) ln (Enterprise Value)	(6) ln (EBIT)	(7) ln (EBITDA)	(8) ln (Earnings Per Share)
ln (AI Tech)	0.111**	0.221**	0.271**	0.14	0.15	0.07	0.09	0.10
	(0.05)	(0.09)	(0.11)	(0.19)	(0.10)	(0.10)	(0.08)	(0.18)
Big firm	0.14	0.28	-0.01	-0.54	0.26	0.03	-0.15	0.46
	(0.13)	(0.23)	(0.32)	(0.51)	(0.30)	(0.35)	(0.22)	(0.59)
ln (AI Tech) x Big firm	-0.02	0.03	0.12	0.36	0.09	0.07	0.18	-0.20
	(0.08)	(0.13)	(0.19)	(0.28)	(0.17)	(0.22)	(0.12)	(0.33)
ln (Non-AI Tech)	0.103**	0.11	-0.14	0.19	0.04	-0.01	-0.07	-0.08
	(0.05)	(0.09)	(0.11)	(0.21)	(0.10)	(0.10)	(0.08)	(0.20)
ln (Capital)	0.237***	0.509***	0.545***	0.655***	0.610***	0.575***	0.669***	-0.05
	(0.03)	(0.03)	(0.04)	(0.08)	(0.04)	(0.05)	(0.04)	(0.08)
ln (Int. Input)	0.621***	0.171***	0.172***	0.131**	-0.01	0.195***	0.177***	0.145***
	(0.03)	(0.03)	(0.04)	(0.06)	(0.04)	(0.04)	(0.03)	(0.05)
Firm Age	-0.001**	-0.001*	0.00	0.004***	-0.002***	0.00	0.00	0.00
	0.00	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Constant	0.926***	1.066**	1.114*	0.34	4.491***	0.36	0.26	1.26
	(0.30)	(0.49)	(0.67)	(1.29)	(0.60)	(0.68)	(0.52)	(1.43)
Observations	423.00	422.00	394.00	286.00	416.00	408.00	413.00	394.00
R-squared	0.93	0.74	0.60	0.47	0.61	0.59	0.77	0.04

Note: The model was run on 8 outcome variables for a filtered sample only including firms with one or more AI technologies.
Robust standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1

Table 15: *Robustness Check with Capital Interaction*

	(1) ln (Revenue)	(2) ln (Gross Profits)	(3) ln (Net Earnings)	(4) ln (Retained Earnings)	(5) ln (Enterprise Value)	(6) ln (EBIT)	(7) ln (EBITDA)	(8) ln (Earnings Per Share)
ln (AI Tech)	-0.553**	-1.153***	-1.270**	-2.479***	-1.437***	-0.93	-1.120**	-1.24
	(0.28)	(0.41)	(0.61)	(0.76)	(0.50)	(0.73)	(0.55)	(1.11)
ln (Capital)	0.151***	0.321***	0.295***	0.14	0.394***	0.411***	0.486***	-0.280**
	(0.06)	(0.07)	(0.11)	(0.15)	(0.09)	(0.11)	(0.10)	(0.13)
ln (AI Tech) x ln (Capital)	0.068**	0.137***	0.157**	0.277***	0.161***	0.11	0.125**	0.14
	(0.03)	(0.04)	(0.06)	(0.08)	(0.05)	(0.08)	(0.06)	(0.11)
ln (Non-AI Tech)	0.04	0.02	-0.189***	-0.12	-0.02	-0.09	-0.11	-0.248*
	(0.03)	(0.06)	(0.07)	(0.14)	(0.06)	(0.07)	(0.07)	(0.14)
ln (Labor)	0.053**	0.170***	0.090**	0.199**	0.210***	0.083**	0.063**	0.091*
	(0.02)	(0.03)	(0.04)	(0.08)	(0.03)	(0.04)	(0.03)	(0.05)
ln (Int. Input)	0.590***	0.114***	0.154***	0.06	-0.101***	0.169***	0.155***	0.132**
	(0.03)	(0.03)	(0.04)	(0.07)	(0.04)	(0.04)	(0.03)	(0.05)
Firm Age	-0.001**	0.00	0.00	0.004***	-0.002**	0.00	0.00	0.00
	0.00	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Constant	1.967***	2.433***	3.156***	5.009***	5.788***	1.83	1.878**	3.823***
	(0.49)	(0.77)	(1.13)	(1.67)	(0.96)	(1.24)	(1.04)	(1.31)
Observations	466.00	464.00	434.00	311.00	459.00	450.00	454.00	434.00
R-squared	0.93	0.76	0.59	0.48	0.63	0.59	0.77	0.06

Note: The model was run on 8 outcome variables for the full dataset of firms.
Robust standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1

Table 16: *Robustness Check with Capital Interaction (AI Users Only)*

	(1) ln (Revenue)	(2) ln (Gross Profits)	(3) ln (Net Earnings)	(4) ln (Retained Earnings)	(5) ln (Enterprise Value)	(6) ln (EBIT)	(7) ln (EBITDA)	(8) ln (Earnings Per Share)
ln (AI Tech)	-0.564**	-1.208***	-0.80	-2.245**	-1.180**	-0.31	-0.52	-1.34
	(0.24)	(0.42)	(0.64)	(0.94)	(0.54)	(0.82)	(0.46)	(1.77)
ln (Capital)	0.135***	0.298***	0.382***	0.19	0.429***	0.528***	0.585***	-0.27
	(0.04)	(0.07)	(0.11)	(0.18)	(0.09)	(0.12)	(0.08)	(0.24)
ln (AI Tech) x ln (Capital)	0.069***	0.148***	0.113*	0.253***	0.140***	0.04	0.07	0.14
	(0.02)	(0.04)	(0.07)	(0.10)	(0.05)	(0.09)	(0.05)	(0.17)
ln (Non-AI Tech)	0.06	0.00	-0.210*	-0.02	-0.10	-0.09	-0.11	-0.14
	(0.05)	(0.09)	(0.11)	(0.21)	(0.10)	(0.11)	(0.08)	(0.20)
ln (Labor)	0.064***	0.171***	0.097**	0.213**	0.213***	0.102***	0.075**	0.07
	(0.02)	(0.03)	(0.04)	(0.09)	(0.03)	(0.04)	(0.03)	(0.06)
ln (Int. Input)	0.598***	0.114***	0.138***	0.02	-0.090**	0.155***	0.148***	0.118**
	(0.03)	(0.03)	(0.04)	(0.07)	(0.04)	(0.04)	(0.05)	(0.05)
Firm Age	-0.001**	0.00	0.00	0.005***	-0.002***	0.00	0.00	0.00
	0.00	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Constant	1.809***	2.731***	2.488**	4.084**	5.789***	0.66	0.87	3.43
	(0.41)	(0.74)	(1.22)	(1.96)	(0.98)	(1.42)	(0.91)	(2.16)
Observations	423.00	422.00	394.00	286.00	416.00	408.00	413.00	394.00
R-squared	0.93	0.76	0.60	0.49	0.63	0.59	0.77	0.04

Note: The model was run on 8 outcome variables for a filtered sample only including firms with one or more AI technologies.
Robust standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1

Table 17: *Robustness Check with Firm Age Interaction*

	(1) ln (Revenue)	(2) ln (Gross Profits)	(3) ln (Net Earnings)	(4) ln (Retained Earnings)	(5) ln (Enterprise Value)	(6) ln (EBIT)	(7) ln (EBITDA)	(8) ln (Earnings Per Share)
ln (AI Tech)	0.09	0.172*	0.292**	-0.25	0.13	0.17	0.12	0.11
	(0.06)	(0.09)	(0.13)	(0.20)	(0.10)	(0.13)	(0.10)	(0.17)
Firm Age	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
ln (AI Tech) x Firm Age	0.00	0.00	0.00	0.006***	0.00	0.00	0.00	0.00
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
ln (Capital)	0.251***	0.522***	0.526***	0.551***	0.624***	0.562***	0.665***	-0.08
	(0.03)	(0.03)	(0.05)	(0.08)	(0.04)	(0.05)	(0.04)	(0.08)
ln (Non-AI Tech)	0.05	0.04	-0.168**	-0.07	0.00	-0.08	-0.08	-0.23
	(0.04)	(0.06)	(0.07)	(0.15)	(0.06)	(0.07)	(0.07)	(0.15)
ln (Labor)	0.060**	0.181***	0.100**	0.254***	0.221***	0.086**	0.069**	0.102*
	(0.02)	(0.03)	(0.04)	(0.08)	(0.03)	(0.04)	(0.03)	(0.05)
ln (Int. Input)	0.589***	0.113***	0.154***	-0.02	-0.097***	0.172***	0.158***	0.132**
	(0.03)	(0.03)	(0.04)	(0.07)	(0.04)	(0.04)	(0.03)	(0.05)
Constant	0.919***	0.29	0.67	1.02	3.305***	0.14	-0.11	1.64
	(0.24)	(0.37)	(0.52)	(0.95)	(0.46)	(0.52)	(0.45)	(1.23)
Observations	466.00	464.00	434.00	311.00	459.00	450.00	454.00	434.00
R-squared	0.93	0.75	0.58	0.47	0.61	0.58	0.76	0.05

Note: The model was run on 8 outcome variables for the full dataset of firms.
Robust standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1

Table 18: *Robustness Check with Firm Age Interaction (AI Users Only)*

	(1) ln (Revenue)	(2) ln (Gross Profits)	(3) ln (Net Earnings)	(4) ln (Retained Earnings)	(5) ln (Enterprise Value)	(6) ln (EBIT)	(7) ln (EBITDA)	(8) ln (Earnings Per Share)
ln (AI Tech)	0.116*	0.272**	0.382**	-0.20	0.16	0.22	0.213*	0.04
	(0.07)	(0.12)	(0.16)	(0.25)	(0.13)	(0.17)	(0.12)	(0.20)
Firm Age	0.00	0.00	0.00	0.00	-0.003*	0.00	0.00	0.00
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
ln (AI Tech) x Firm Age	0.00	0.00	0.00	0.005**	0.00	0.00	0.00	0.00
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
ln (Capital)	0.244***	0.532***	0.561***	0.606***	0.647***	0.593***	0.689***	-0.05
	(0.03)	(0.03)	(0.04)	(0.08)	(0.04)	(0.05)	(0.04)	(0.08)
ln (Non-AI Tech)	0.05	-0.01	-0.221**	-0.01	-0.11	-0.10	-0.12	-0.15
	(0.05)	(0.09)	(0.11)	(0.21)	(0.10)	(0.11)	(0.08)	(0.19)
ln (Labor)	0.070***	0.185***	0.108***	0.240***	0.226***	0.105***	0.081***	0.09
	(0.02)	(0.03)	(0.04)	(0.08)	(0.03)	(0.04)	(0.03)	(0.06)
ln (Int. Input)	0.597***	0.112***	0.137***	0.01	-0.089**	0.156***	0.149***	0.117**
	(0.03)	(0.03)	(0.04)	(0.07)	(0.04)	(0.04)	(0.04)	(0.06)
Constant	0.713**	0.35	0.62	0.47	3.627***	-0.12	-0.27	1.18
	(0.28)	(0.46)	(0.64)	(1.16)	(0.56)	(0.63)	(0.48)	(1.60)
Observations	423.00	422.00	394.00	286.00	416.00	408.00	413.00	394.00
R-squared	0.93	0.75	0.60	0.49	0.62	0.59	0.77	0.04

Note: The model was run on 8 outcome variables for a filtered sample only including firms with one or more AI technologies.
Robust standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1