Jump Starting the AI Engine: The Complementary Role of Data and Management Practices*

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Abstract

Artificial intelligence is transforming business and society, but evidence that AI is boosting productivity is limited. To address this gap, I construct measures of AI investment for a large longitudinal sample of publicly-traded U.S. firms, as well as their data and management practices. I find that the average effects of AI investment on the firms' productivity and stock market performance are noisy. However, long-differences regressions suggest that the benefits of AI become evident following an implementation lag period and instrumental variable regressions suggest a strong and sizeable positive impact. I also find significant heterogeneity across firms: The distribution of AI investment is skewed, and the impact of AI is only salient for a subgroup of distinctive firms. In particular, AI has a positive effect for firms with more intensive data or management practices, while the marginal effect of AI may not be statistically different from zero if the complementary practices are low. Furthermore, the performance gap persists and widens over time. These findings highlight the complementary role of data and management in leveraging AI investment to boost firms' productivity and market value.

Keywords: artificial intelligence, information technology, value of data, management practice, firm performance, complementarity

*I have received helpful comments from Seth Benzell, Erik Brynjolfsson, Avi Goldfarb, Kyle Handley, Wang Jin, Daniel Rock, Robert Seamans, Yue Maggie Zhou and seminar participants at the CIST, Stanford, CUHK, HKUST, NUS, Stevens, UBC Sauder, and Tilburg. I am grateful to Wang Jin for the help on BGT-Compustat bridge. Anthony Weng at Stanford provided invaluable research assistance. All errors are my own.

1 Introduction and Motivation

Artificial Intelligence (AI) has infiltrated all aspects of business and daily life, from fraud detection to content generation (e.g., DALL·E by OpenAI), from navigation services to gaming competitions (e.g., Alpha Go by DeepMind). Such wide applications are expected to drive innovation, business growth, and standards of living (Russell (2022)). This is because AI, as a general-purpose technology, is believed to have the potential to boost productivity and create value, which can diffuse through the economy to transform organizations, the future of work, and society at large (Bresnahan and Trajtenberg (1995); Goldfarb, Taska, and Teodoridis (2022)). Consistently, existing studies suggest a positive impact of AI on firm growth and innovation (Griliches (1957); Cockburn, Henderson, and Stern (2019); Babina et al. (2021)). However, despite the hype over AI investment among firms, evidence that AI contributes to productivity growth and value creation has been limited (Ransbotham et al. (2017); Agrawal, Gans, and Goldfarb (2019); Furman and Seamans (2019); Brynjolfsson, Rock, and Syverson (2021)). Afterall, "85 percent of AI projects will deliver erroneous outcomes" according to a recent Gartner report[1]. To name just a few potential reasons for this gap, the output statistics do not account for intangibles (Syverson (2017)). The adoption costs of AI are prohibitively high and the learning curve is steep. Alternatively, some benefits of AI arrive following a J-curve process (Brynjolfsson, Rock, and Syverson (2021)), which offsets the short-term effects.

To address this gap, I use an instrumental variable (IV) approach to uncover a causal relationship between firms' AI investments and their productivity and stock market performance. To further reduce the noise, I investigate a unique mechanism through which the impact of AI may defer across firms: I argue that firms may need complementary data and management practices to "jump start" the AI engine and unlock its potential to improve productivity and stock market valuation.

To be more specific, I first merge the Burning Glass Technologies (BGT) job postings database and the Compustat database from 2010 to 2020. Using the matched sample, I compute each U.S. publicly traded firm's AI investment using its postings of AI skill[2] demand as a share of its

[1] https://www.gartner.com/en/newsroom/press-releases/2018-02-13-gartner-says-nearly-half-of-cios-are-planning-to-deploy-artificial-intelligence

[2] AI skills are manually defined as Image Analysis, Artificial Intelligence, Natural Language Processing (NLP), Data Mining and Machine Learning.

total job postings.[3] I then estimate the average effects of AI investment on a wide range of firm outcomes, including total factor productivity (TFP), total sales, market value, and Tobin's Q. I find that the average effects of AI investment are positive but noisy. This noise can be partly due to issues such as omitted variables and reverse causality that would endogenize firms' choice of AI investment, similar to endogeneity issues in firms' technology adoption choices (Tambe and Hitt (2012); Nagle (2019)). That is, unobserved shocks might simultaneously shift both firm outcomes and AI investment. Better performing firms might be more likely to invest in frontier technologies or firms lagging behind might invest more radically in AI, hoping to catch up.

To address the endogeneity issue, I develop a long-differences strategy to absorb short-term serially correlated shocks and construct an IV by multiplying (1) industry-level ex-ante exposure to AI based on occupation composition (Felten, Raj, and Seamans (2021)) and (2) the aggregate employment share of data service industry (Jin and McElheran (2017); Jin (2022)) adjusted by the inverse of price of data storage devices in a given state, industry, and year. Specifically, I compute the share of high AI exposure (top quartile) occupations based on the score constructed by Felten, Raj, and Seamans (2021) at 2009 industry (4-digit NAICS) level. Year 2009 is chosen since massive AI investment at firm-level has not yet started. Thus, this is relevant to ex-post AI investment but exogenous to ex-post firm performance. This approach is similar to other works on AI investment (Babina et al. (2021)) as well as instrumenting robot investment (Graetz and Michaels (2018); Dixon, Hong, and Wu (2021)). In addition, the share of data service industry in a state is relevant to the AI investment made by the firms in the state, yet the location of these providers are conditionally exogenous to local demand as the location choice of data service providers are more efficiency-driven than demand-driven as argued in Armbrust et al. (2009) and Jin and McElheran (2017). I further adjust the data industry exposure with the inverse of price of data storage devices, which is also likely to be exogenous to particular firm performance. The IV estimates point to a positive and sizable causal impact of AI investment on firm productivity, and stock market performance: One standard deviation shock to AI investment leads to an increase of 19.7 log points in TFP (67% and 23% of sample mean and standard deviation, respectively, in TFP), as well as an increase of 17.3 log points in Tobin's Q (34% and 31% of sample mean and

[3]This construct follows a recent stream of literature that uses firms' skill demand to derive technology adoption and accumulation (Atalay and Sarada (2020); Abis and Veldkamp (2020); Acemoglu et al. (2020); Alekseeva et al. (2021); Babina et al. (2021); Bloom et al. (2021))

standard deviation, respectively, in Tobin's Q).[4]

The different results estimated from the regular and IV regressions suggest that the impact of AI is only salient within a subgroup of distinctive firms. It could also suggest that the IV estimation of returns to AI reflects the returns to the investment of both direct AI investments and its complements, as these investments are usually simultaneous. To further uncover the noise, I find that the distribution of AI investment[5] is skewed and explore heterogeneity across firms in the intensity of data and management practices. Specifically, I follow Saunders and Tambe (2015) and Handley and Li (2020) to construct firm-level data practice. I extract data-related phrases from three industry reports (Manyika et al. (2011); Manyika et al. (2013); Henke et al. (2016)) and map them to firms' 10-K and 10-Q filings. I also follow Abis and Veldkamp (2020) to measure firm management practice. I compute firm-level stock of Computer and Information Systems Managers recursively (using BGT occupation demand as flows and weighted job separation rate of the occupation[6]). Other management occupations (e.g., legislators, financial managers, construction managers, etc.) are excluded since they are not directly in charge of or related to the operations of IT and AI within the organization.

Using these measures I first find a high correlation between AI investment and intensity in data and management practices. I then confirm a strong complementarity effect between data/management practices and AI investment on productivity and market value performance.[7] The results further suggest that the "mis-coordinated" practices, that is when high AI investment is associated with low data/management practice within the firm, or vice versa, could yield null performance.[8] The marginal effects of AI on some performance measures maybe not statistically different from zero if the complementary practices are low.[9] A one standard deviation increase in AI investment (about 2 percentage points) results in an additional 1.4 log points increase in TFP and an additional 2.2

[4]The large magnitude of IV estimates is consistent with Angrist and Pischke (2009) and Wooldridge (2010) as the IV regression tries to capture the local effect of AI investment, which could come from firms whose return to AI is larger than average.

[5]This is consistent with findings in Zolas et al. (2020).

[6]The separation rate is constructed by a weighted average of industry level job separation rate extracted from the Job Opening and Labor Turnover Survey (JOLTS) with share of industry contributing to the Computer and Information Systems Managers occupation.

[7]A formal discussion of test of complementarity can be found in Athey and Stern (1998) and Brynjolfsson and Milgrom (2013).

[8]It could yield even negative performance if the magnitude of "mis-coordination" is large.

[9]I define high vs low data/management practices as the top and bottom quartile of the sample with respective to data/management practices measures.

log points increase in Tobin's Q for firms with high data practice compared to those with low data practice, and an additional 2.8 log points increase in TFP and an additional 3.2 log points increase in Tobin's Q for firms with high data practice compared to those with low management practice. All the results are robust to a wide range of control variables and firm and year fixed effects. To further explore the role of complements in the long-term, I split the sample into high vs low data (management) complements and run long-differences separately. The results suggest that complementary practices still play important roles in the long-run. Firms who invest in complementary practices enjoy long-lasting performance lead in returns to AI investment. And the "performance gap" could persist or even widen. These findings support a systematic need for complementary data and management practices to AI investments beyond existing studies, including workplace organizations (Bresnahan, Brynjolfsson, and Hitt (2002); Brynjolfsson, Jin, and McElheran (2021)), technical skills (Tambe (2014)), and organizational capital (Brynjolfsson, Hitt, and Yang (2002)).

In sum, this study establishes a link between AI investment and firm productivity and stock market performance. It further suggests that the performance boosts from AI investment is driven by a subgroup of distinctive firms. Then I identify that these firms are intensive in complementary data and management practices that help start the "AI engine".

The remainder of this paper is organized as follows. Section 2 discusses related literature. In Section 3, I describe the underlying data sources and the construction of the measures. In Section 4, I develop the conceptual framework and the empirical strategy. Section 5 presents empirical results. Section 6 concludes.

2 Related Literature

This paper makes a few contributions to the existing literature. First, a growing body of work in IT and productivity has investigated the adoption and impact of artificial intelligence. To understand the determinants of AI diffusion and its outcomes, there have been efforts to create fine measurements of AI using: O*NET task descriptions (Brynjolfsson, Mitchell, and Rock (2018); Felten, Raj, and Seamans (2021)), online job postings (Babina et al. (2021); Alekseeva et al. (2021)), patents (Webb (2019); Miric, Jia, and Huang (2022)), and government or private sector survey data (Chui and Malhotra (2018); Zolas et al. (2020)). Similar to other types of IT resources, such as IT

infrastructure (Bharadwaj (2000)), computers (Weill (1992); Brynjolfsson and Hitt (2003)), and IT workers (Tambe and Hitt (2012, 2014)), most studies point to a positive impact of AI investment. Rock (2019) has found positive returns to AI skills (e.g., Google's TensorFlow) for firm valuation, and Babina et al. (2021, 2022) have focused on the impact of AI on firm growth, innovation, and workforce composition. However, as I find in this study, the benefits of AI are not distributed evenly. This could provide some micro-level explanations for the rise of "super star" firms and the concentration of market power among firms with advanced information technology (Autor et al. (2020)).

Second, prior studies have discovered persistent heterogeneity across firms in the relationship between digital investment and performance (Bennett (2020)). Particularly, Tambe et al. (2020) apply the Quantity Revelation Theorem to calculate the stock of digital capital (including AI) with LinkedIn data and find that digital capital has accumulated disproportionately within a small set of distinctive firms, and the returns are mostly captured by these firms. This might be fed by the heterogeneity in firm resources and capabilities that complement investment in technology. A key factor in firm resources is data, which is like the fuel to the AI engine (*Economist* (May 6, 2017)[10]). My findings suggest that firm resources and capabilities in data practices (e.g., data retrieval, storage, management, and analysis) are valuable for firms to harness the benefits of AI investments. Researchers have been unravelling the value of data in other related settings: Tambe (2014) documents the productivity effect of data processing skills such as Hadoop and Spark; Saunders and Tambe (2015) measure data practice at firm-level and exploit its correlation with market values and Tobin's Q; Wu, Lou, and Hitt (2019) and Wu, Hitt, and Lou (2020) demonstrate that investment in data analytics drives innovation; Crouzet and Eberly (2019) and Abis and Veldkamp (2020) suggest data intangibles shape corporate physical investment, long-run outputs, and industry evolution; Jones and Tonetti (2020) and Bergemann, Bonatti, and Gan (2022) study how the distribution and ownership of data could improve or hurt consumer welfare; Farboodi et al. (2022a,b) assess how data reflect information about the financial market and help investors make decisions. This paper contributes to this stream of literature by highlighting the value of data practices as complementary to AI investments and explaining the skewed distribution of AI adoption and returns to AI.

[10]To quote the *Economist* article, "The world's most valuable resource is no longer oil, but data."

Finally, my findings suggest the importance of firm capability in management practices for AI investment. Prior work emphasizes that technology (esp. GPT) deployments and outcomes depend on firm's practices in managerial intangibles (Saunders and Brynjolfsson (2016)), such as capacity to handle organizational adjustment costs and frictions (Bresnahan and Greenstein (1996); Feigenbaum and Gross (2021)). Seminal works by Milgrom and Roberts (1990), Milgrom and Roberts (1995), and Brynjolfsson and Milgrom (2013) provide theoretical basis to the literature on complementarity between technology adoption and management practices. There is also a rich set of empirical explorations in this area: Ichniowski, Shaw, and Prennushi (1995) and Bloom, Sadun, and Van Reenen (2012) emphasize the importance of human capital and people management; Black and Lynch (2001) and Bresnahan, Brynjolfsson, and Hitt (2002) study how workplace (re)organization interacts with IT adoption in the production process; Brynjolfsson, Hitt, and Yang (2002) asses the value of computer and organizational structure's contribution to market value; Choudhury, Starr, and Agarwal (2020) study how artificial intelligence and strategic management of human capital complementarities mitigate the bias resulting from strategic behavior. Similar to this paper, Brynjolfsson, Jin, and McElheran (2021) rely on high-quality establishment-level Management and Organizational Practices Survey (MOPS) data to identify complementary practices for predictive analytics in the manufacturing sector. My work extends this line of research by identifying the complementary role of management practices to AI investments in boosting productivity and stock market performance.

3 Measurement and Data

Prior work on AI investment, value of data, and management practices has been partially limited by the availability of firm-level data. This paper follows recent developments in the literature to construct measures of investment in artificial intelligence (Alekseeva et al. (2021); Babina et al. (2021)), data practices (Saunders and Tambe (2015)), and management practices (Abis and Veldkamp (2020)), and then match the constructed measures with Compustat to obtain data on balance sheet and financial information. In this section, I describe how multiple data sources are processed, present descriptive patterns, and summarize the data sample (see Table 1).

3.1 Investment in Artificial Intelligence

The main data source for analyzing the investment in artificial intelligence is the job postings data from Burning Glass Technologies (BGT). BGT, as one of the leading vendors of labor market data provider, is arguably claimed to cover the near-universe of job postings in the U.S. It constantly tracks over 200 million online job vacancies by scanning more than 40,000 distinct online platforms since 2007.[11] Each piece of job posting is parsed and de-duplicated, and offers details such as job title, job occupation, Standard Occupational Classification (SOC) code, employer name, and job location. A key advantage of BGT data is the profiles of skills required to job from the potential employee. The skills are mapped to a detailed skill taxonomy, which consists of 3 levels of granularity including skills, skill clusters, and skill families.[12] The hierarchical structure of the BGT skills data is as follows. There are approximately 16,000 skills, nested within 658 skill clusters, nested within 28 skill families. It allows me to examine the fine or coarse skill requirements of specific jobs, occupations, and firms.

Job-level skill requirements data has been utilized to track technology diffusion (Bloom et al. (2021)), frontier investment and stock of analytical skills, such as AI and IT in general (Rock (2019); Tambe et al. (2020); Babina et al. (2022)). The model of vintage human capital (Chari and Hopenhayn (1991)) predicts rapid turnover and accumulation of skills drive the diffusion of new technology and push firms to the technological frontier. As AI technology requires highly-specialized human capital (Tambe (2014)) and AI skills are digital and emerging (Deming and Kahn (2018)), BGT online job postings database becomes a natural and adequate candidate to construct firm-level AI investment through job demand. I follow recent studies (Alekseeva et al. (2021); Babina et al. (2021)) and extract information regarding firm's investment and adoption of artificial intelligence from their skill demands, and propose a skill-based measure of AI investment at the firm level. Specifically, I focus on AI-related skill clusters including {*Image Analysis, Artificial Intelligence, Natural Language Processing (NLP), Data Mining, Machine Learning*}[13], and build the main measure of AI investment in firm i at time t as the share of the entire human capital investment, i.e., the ratio of job postings requesting AI skills against the total number of job

[11] The BGT dataset obtained contains details on job vacancy postings from 2010 to 2020.

[12] Technologies (2019) provides a detailed overview of a rule-based skill parser on which the skills are annotated.

[13] The skill clusters are manually selected, which is consistent with the recent literature (Alekseeva et al. (2021); Rock (2019); Goldfarb, Taska, and Teodoridis (2022)).

postings:

$$\text{AI Investment}_{it} = \frac{\text{Number of Job Postings Requesting AI Skills}_{it}}{\text{Total Number of Job Postings}_{it}} \times 100.$$

This measure is appealing for the following reasons. First, firm-level data usually overlook intangible firm capital (Atalay and Sarada (2020)), such as technical skills. However, firms rely on skilled human capital to make AI technology effective. One might be concerned that firms choose to outsource their AI analytics to tech consulting or cloud vendors. Even in this case, it is essential for the firm to hire AI experts for communication and analysis so that the outsourced jobs are tailored to the firm's specific needs. Second, the ratio of AI to total skill demand proxies the intensity of AI investment. The intensity measure is closer to the investment rate, especially after absorbing firm and time fixed effects in the empirical exercises.

To obtain firm-level information on balance sheets, market value, and sales, etc., I use the Compustat database. However, BGT does not contain a Compustat firm identifier, I follow Bai et al. (2021) and Jin (2022) to bridge the two databases using a fuzzy matching approach, which relies on historical Orbis data to take into account the cases where firm subsidiaries have different names than their parents (e.g., LinkedIn and Microsoft). This approach achieves a higher matching rate, and successfully matches more than 4,000 unique firms (BGT firm name to GVKEY).[14]

Although previous studies have justified (theoretically and empirically) the validity of the measure, it is worth discussing several sources of measurement error. First, the job postings data from BGT captures labor demand at the firm-level, which gauges flow of human capital rather than the stock of human capital. Nevertheless, there is no publicly available data on job turnover at the firm-level[15] and AI jobs are likely to be listed across multiple occupations. As such, the alternative of constructing AI human capital stock from aggregate separation rates could be even more noisy. Given the high annual job separation rate at the aggregate level[16], it is reasonable to measure firm-level AI investment from the demand side as the jobs always need to be filled. Second, the measure is exposed to potential noise due to the filling rate of the job postings. A particular job posting may result in failed hire or multiple hires or even different hires. The rate and time length

[14] In the sample of analysis, the number of unique firms reduces to a little above 3,000 since matching with SEC EDGAR loses some observations.

[15] The job separation rate at occupation level is available, which will be discussed in later sections.

[16] Usually higher than 40%, according to https://www.bls.gov/news.release/jolts.t16.htm.

to fill a job posting also varies across firms and time. Therefore, BGT data may not represent the exact profile of the actual employment and this issue is again hard to adjust without detailed firm-level human capital stock or separation data. However, several recent studies (Babina et al. (2022); Rock, Tambe, and Wang (2022)) that rely on LinkedIn like human capital stock database (such as Cognism and Revelio Labs) find that the human capital flow data generated from the actual employment stocks correlates strongly with job vacancies data (e.g. BGT) and the results generated from the two are quatitatively similar. Third, firms might post jobs strategically based on the understanding of their business needs, demand from their competitors, and labor market tightness. So that it is possible that firms demand more skills/positions than needed. This is challenging to detect and resolve without the ground truth of actual skills employed within the firm. It helps alleviate this concern to normalized by the total number of skills/postings, as defined above.

Overall, the online job postings data provides detailed information and a dynamic nature of AI talend across firms and time. In Figure 1, I provide descriptive patterns of AI investment over time and by industry. Panel (a) plots the time trend of AI investment averaged over all the firms in the matched sample. It is clear that AI investment has been rising steadily and significantly from around 0.4 percentage points to more than 1 percentage points from 2010 to 2020. This finding is consistent with the drastic increase in the scientific, educational, and business applicable developments in the field of artificial intelligence. I also find AI investment is zero in more than half of the observations of the sample which covers publicly traded firms. This result is consistent with Zolas et al. (2020), which finds the adoption pattern of AI is skewed and biased towards a small distinctive set of firms in a sample representative of the economy. Panel (b) lists the average AI investment by industry. It indicates that AI investment is concentrated in several industries, including information technology, services (professional and business services, educational services, etc.), manufacturing, and finance and insurance. Sectors that rely more traditional skills lack AI investments, such as accommodation and food, art and entertainment, and mining and utilities. This piece of evidence partially confirms the validity of the measure. To further understand the pattern of AI investment in human capital, I correlate AI investment with a series of firm characteristics, including market value, total employment, capital stock, total asset, total sales, Tobin's Q, etc., all controlling for firm and year fixed effects, reported in Table 2, and find that AI investment is associated with

larger firms and higher market valuation (higher Tobin's Q)[17], which is consistent with Tambe et al. (2020).

3.2 Data Practice

As the fuel to the AI engine and the complementary element, data is essential to the success of AI investment. However, it is notoriously difficult to track data practice at the firm level. In this paper, I closely follow Saunders and Tambe (2015) and Handley and Li (2020) to measure the retrieval, storage, management, and analysis of data using textual analysis of highly cited industry reports on data practices in the business environment and firms' SEC EDGAR 10-K and 10-Q reports. All publicly traded firms are required to submit annual reports (10-K) and quarterly reports (10-Q) to U.S. Securities and Exchange Commission (SEC), which must comply with certain requirements. Each document contains a series of descriptions on firm business, risk factors, financial information, management's discussions, etc. The SEC EDGAR filings are consistent and standardize and are an attractive source to understand corporate condition, policy, and behavior, and have been widely utilized in the literature (e.g., competition, Hoberg and Phillips (2016); uncertainty, Baker, Bloom, and Davis (2016); Handley and Li (2020); innovation, Bellstam, Bhagat, and Cookson (2021), and others).

I clean and parse the SEC EDGAR filings by removing all stop words, e.g. "a", "an", "the", "of" etc., titles, figures, and tables, and stem all words under Porter Stemming Algorithm. Then I match the filings against a dictionary of data-related unigrams and bigrams from all 10-K, 10-Q reports and their amendments each year. The entire textual sample includes 286,113 documents — all 10-Q and 10-K forms, their variations, and amendments — filed by 9,052 firms from 2010 to 2020. Each filing must be matched with a Compustat firm through the SEC EDGAR firm identifier: Central Index Key (CIK).[18]

Following Saunders and Tambe (2015), I derive the primary lexicon from industry reports by the McKinsey Global Institute, *Big Data: The Next Frontier for Innovation, Competition, and Productivity* (Manyika et al. (2011)), as well as two additional more recent reports by the same

[17]Sales and Tobin's Q are omitted in column (8) due to the concern of collinearity: sales is a function of employment and capital stock (esp. in productivity estimation), and Tobin's Q is computed from market value and total asset.

[18]The sample size get reduced when measures extracted 10-K and 10-Q forms are aggregated to firm-year pairs and the sample is merged with Compustat-BGT data.

institute, *Open data: Unlocking innovation and performance with liquid information* (Manyika et al. (2013)), and *The Age of Analytics: Competing in a Data-Driven World* (Henke et al. (2016)). Similar to the cleaning process of the SEC EDGAR filings, the industry reports are first cleaned and parsed by removing all stop words, and each word is stemmed. Then I collect all possible bigrams that combines with the appearance of word "*data*", as well as unigrams that contains "*data*" (e.g., *metadata, database, dataset*). The full list contains 2032 unique data-related bigrams and unigrams, and the ones that appear more than 5,000 times in the sample are reported in Table 3.[19] Finally, the lexicon of the data-related terms are matched to each 10-K and 10-Q document parsed in the previous steps. To help understand the source of the measure, I provide following contextual examples of well-known companies from different sectors:

JPMorgan Chase & Co (primary sector - finance and insurance): Data Analysis

> "***Data sources*** used in VaR models may be the same as those used for financial statement valuations. However, in cases where market prices are not observable, or where proxies are used in VaR historical time series, the sources may differ. In addition, the daily ***market data*** used in VaR models may be different than the independent ***third-party data*** collected for VCG price testing in their monthly valuation process (see Valuation process in Note 3 for further information on the Firm's valuation process). VaR model calculations require ***daily data*** and a consistent source for valuation and therefore it is not practical to use the ***data collected*** in the VCG monthly valuation process." (JPMorgan Chase & Co, 2014 10-K, Item 7. MD&A)

Hewlett-Packard Company (primary sector - manufacturing): Big Data

> "Our ***big data*** platform, Haven, brings these unique assets together for processing and understanding ***machine and sensor data***, ***business data*** and unstructured human information. A growing ecosystem of customers, partners and developers use this platform to build ***big data driven*** analytic applications. Our Software segment also leverages Haven's unique analytic assets to deliver purpose-built solutions for a variety of markets, including application testing and delivery, ***big data analytics*** and applications, IT Operations Management, and enterprise security. These solutions are designed for businesses and enterprises of all sizes, and are available via on-premise, as well as via SaaS and hybrid delivery models. Software's Haven ***big data*** platform and purpose-built applications are augmented by our support and professional services offerings in order to provide an end-to-end solution to customers." (Hewlett-Packard Company, 2015 10-K, Item 1. Business.)

[19] Following Saunders and Tambe (2015), I include all inverses of the stemmed bigrams, e.g. "avail data" and "data avail". Since the context of financial information can use the word "data" to represent firm data reported to the SEC, rather than describing the data practices within the firm, I remove the following items in the analysis: "supplementary data", "financial data", "sheet data", "interactive data", "income data", "operating data", "per share data", "accounting data", "data accounting", "asset data".

Amazon.com, Inc (primary sector - retail trade): Data Center

> "We own and lease our corporate headquarters in Seattle, Washington. Additionally, we own and lease corporate office, fulfillment, sortation, delivery, warehouse operations, ***data center***, customer service, and other facilities, principally in North America, Europe, and Asia." (Amazon.com, Inc, 2017, 10-K, Item 2. Properties)

IQVIA Holdings Inc (primary sector - professional, scientific, and technical services): Data science

> "We apply human ***data science*** – leveraging the analytic rigor and clarity of ***data science*** to the ever-expanding scope of human science – to enable companies to reimagine and develop new approaches to clinical development and commercialization, speed innovation, and accelerate improvements in healthcare outcomes. Powered by the IQVIA CORE™, we deliver unique and actionable insights at the intersection of large-scale analytics, transformative technology and extensive domain expertise, as well as execution capabilities." (IQVIA Holdings Inc, 2019 first 10-Q, Item 2. Management's Discussion and Analysis of Financial Condition and Results of Operations)

Pinterest Inc (primary sector - information technology): Data Asset

> "As of December 31, 2019, our Pinners saved 240 billion pins across five billion boards. We call this ***body of data*** the Pinterest taste graph. Machine learning and computer vision help us find patterns in the data. We then understand each individual Pin's relationship not just to the Pinner who saved it, but also to the ideas and aesthetics reflected by the names and content of the boards where it's been pinned. We believe we can better predict what content will be helpful and relevant because Pinners tell us how they organize ideas. The Pinterest taste graph is the first-party ***data asset*** we use to power our visual recommendations." (Pinterest Inc, 2020 10-K, Item 1. Business.)

The excerpts highlight several points. First, data practice has spread into sectors beyond information technology, including finance and insurance, service, and retail trade. Second, data practice covers a wide range of topics, as represented in the context. JPMorgan Chase and IQVIA rely on data sources and data science analytics for analysis and making predictions. Hewlett-Packard reports and describes their big data product. Amazon and Pinterest take data as tangible (data center) or intangible asset. Third, these discussions can take place outside business and MD&A sections, e.g. Amazon 2017 10-K on data center. I focus on parsing the entire 10-K and 10-Q documents so that such discussions would not be missed.

To derive the measure of data practice at the firm level, I aggregate 10-K and 10-Qs within firm i and year t to obtain total count of data-related terms. Then I normalized this count by total

number of meaningful words (stop words removed) to compute

$$\text{Data Practice (simple weight)}_{it} = \frac{\text{Total data-related terms}_{it}}{\text{Total number of meaningful words}_{it}}.$$

To account for the importance of the term within the document and across the collection of the documents, I weight each term w based on TF-IDF (term frequency-inverse document frequency) weights following Jurafsky and Martin (2009) and Saunders and Tambe (2015):

$$w_{wit} = (1 + \log(TF_{wit})) \times (1 + \log(\frac{N_t}{DF_{wt}})).$$

The variable TF_{wit} is the number of occurrences of term w in firm i year t, N_t is the total number of firms in year t, and DF_{wt} is the number of firms in year t that use the term w for at least once.[20] Similar to the simple weights, $(1 + \log(TF_{wit}))$ weights each term by number of occurrences. The expression $(1 + \log(\frac{N_t}{DF_{wt}}))$ gives more weight to terms that are less common within year t. Thus,

$$\text{Data Practice}_{it} = \frac{\sum_w w_{wit}}{\text{Total number of meaningful words}_{it}} \times 100.$$

The rise of data in the new economy is shaping business growth and is reflected in firm resources, decisions, and corporate reports. This pattern can be tracked by the measure of data practice. Panel (a) in Figure 2 plots the average data practice measure of all the firms in the sample from 2010 to 2020. The data practice measure surges rapidly from 2010 to 2015 and remained relatively flat and high afterwards. The bottom panel of Figure 2 decomposes the measure into sectors. Like the industry decomposition of AI investment, information technology and service sectors are the major consumers of data practice. Health care, retail trade, finance, and manufacturing sectors also conduct significant data practices. To connect data practices with firm attributes, I regress data practice on a set of measures of firm valuation, size, and innovativeness and report the results in Table 4. Firms with more intensive data practice are larger in employment, valued higher in the stock market (market value and Tobin's Q), and more innovative (higher R&D investment rate). Higher capital stock and sales does not necessarily associate with higher data practice, and total

[20] I exclude the extremely rare occurrences, e.g., appear less than 5 firms, to remove outliers. The results are robust with or without such practice.

asset is negatively associated with data practice in the kitchen sink regression in column (8). It suggests that the data practice measure does not emerge in large firms only, but data practice intensive firms innovate more intensively and are awarded by the stock market.

3.3 Management Practice

The third key variable to this study is management practice. As discussed in Section 3.2, the data inputs for AI modeling needs to be cleaned, processed, and structured. Furthermore, the AI modeling needs to be planned, coordinated, and tailored towards the business urges. Both exercises rely on the judgement from human capital that bridges the data and artificial intelligence analysis with managerial practices to meet the requirements of the business goal of the firm and cast this technology to business projects. To gauge the management practice of firms, I borrow the idea from Abis and Veldkamp (2020) to create a firm-level stock of Computer and Information Systems Managers (SOC code 11-3021) with perpetual inventory method. According to the U.S. Bureau of Labor Statistics (BLS), computer and information systems managers "plan, direct, or coordinate activities in such fields as electronic data processing, information systems, systems analysis, and computer programming"[21], and satisfy the management practice requirements for AI investment.

Specifically, I aggregate job demand in the computer and IS manager occupation (SOC code 11-3021) at the firm-year level from the BGT database[22] to measure the flow of management practice human capital. To generate a stock measure I require a depreciation rate, which in this application is the job separation rate.[23] The government statistics do not provide detailed occupation-level job separation measures at a great detail. So I rely on two industry-occupation level databases to approximate the separation rate of the computer and IS manager occupation (SOC code 11-3021). To obtain job separation rate, I source from the Job Openings and Labor Turnover Survey (JOLTS). The JOLTS program, published by the BLS, produces data on job openings, hires, and separations at both national and industry-level on a monthly, quarterly, and annual basis. Thus for each industry j in year t, one can get the value of job separation rate job_sep_{jt}. Then I need to map the occupation data to industries to compute the weighted occupation-level separation rate as the

[21] https://www.bls.gov/oes/current/oes113021.htm

[22] The advantages and concerns of using BGT data have been discussed extensively in Section 3.1.

[23] Note that we assume a perfect filling rate of job postings due to lack of detailed data. However, this assumption is not hugely unrealistic since the U.S. job market is usually very tight, especially in technical positions, such as the one this paper is measuring.

approximate. The Occupational Employment and Wage Statistics (OEWS) help fill the gap. The OEWS program produces employment and wage estimates annually for nearly 800 occupations for the nation, states, and industries[24], so that one can calculate the employment share of industry j within all the computer and IS manager job at year t, sh_cism_{jt}. Therefore, the job separation rate of computer and IS managers in year t, λ_t, is defined as a weighted average of job separation rate

$$\lambda_t = \sum_j job_sep_{jt} \times sh_cism_{jt}.$$

Built on the job separation rate, the human capital stock of management practice is constructed through perpetual inventory method:

$$\text{Management Practice}_{it} = (1-\lambda_t)\text{Management Practice}_{it-1} + \text{Mgmt Human Capital Flow}_{it-1},$$

with $\text{Management Practice}_{i,2010} = \text{Mgmt Human Capital Flow}_{i,2010}$.[25]

The trend and industry decomposition of firms' management practice (averaged) are presented in Figure 3. It is natural to observe an increase in the trend due to the fact that management practice is constructed by the perpetual inventory method. However, the separation rate is usually quite high[26], the pattern that the human capital accumulated management practice measure keeps rising into the mid 2010s tells that even without an accurate observation of the initial stock, firms' intensity in management practice is climbing in recent years. Service and information technology industries stock very high value of management practice. It is worth noticing that health care and social assistance has the highest intensity in computer and IS managers stock. Table 5 shows the results of regressing management practices on firm characteristics. The regression specifications are the same as in the regressions Table 2 and 4. I find that management practice is (naturally) more intensive among firms with larger market value, total employment, capital stock, total asset, and sales.

[24] The bridge between OEWS industries (NAICS) and JOLTS can be found at https://www.bls.gov/jlt/jltnaics.htm.

[25] Management human capital flow is lagged one year to allow for the usual gap between job posted and position filled/entered.

[26] It is not uncommon to observe 40% or above separation rate.

3.4 Firm Performance and Compustat

I rely on the Compustat database to obtain measures of firm performance and control variables. The detailed definitions can be found in Table A1. AI investment and management practice are matched with Compustat through the BGT-Compustat bridge derived through name-address fuzzy matching. Data practice is matched with Compustat through the firm identifier, CIK, and year. The final sample ranges from 2010 to 2020, yielding more than 24,000 observations with more than 3,000 unique firms.

4 Empirical Approach

This section discusses the empirical approaches of the estimation of AI investment on performance and the complementarity tests.

4.1 Performance Estimation

To explore the impact of AI investment on firm performance, I first estimate the average effect based on the conventional approach. The baseline estimation equation is

$$Y_{it+1} = \alpha_0 + \beta_{AI} \times \text{AI Investment}_{it} + Controls_{it} + \alpha_i + \alpha_t + \epsilon_{it}, \tag{1}$$

where i indexes firm and t indexes year. The dependent variable Y_{it+1} represents several performance measures, including log(Market Value), log(Tobin's Q), log(Sales), and TFP. AI Investment$_{it}$ is defined as in Section 3.1. The AI investment variable is lagged one year relative to the performance variables to allow for the gap between skills demanded and skills equipped within firm as well as the time of training and adjustment. Control variables include log(Employment), log(Capital Stock), which are standard inputs of the productivity estimation, and rate of capital investment, which governs the physical capital part of the input of investment-q estimation. R&D investment rate is also included to account for the potential use of AI investment in innovation rather than production. All specifications also include firm fixed effects α_i time fixed effects α_t to absorb any other unobservable firm characteristics and aggregate shocks that might influence Y_{it}.

The primary interest is on β_{AI}, which represents the impact of AI investment on the perfor-

mance measures, i.e. productivity and stock market valuation. One should expect $\beta_{AI} > 0$ if the average effect of AI investment over the entire population of firms is positive. However, technology investment (AI investment in particular in this paper) could suffer from endogeneity concerns in the OLS estimation, biasing the interpretation of β_{AI}. First, unobservable shocks could simultaneously shift both firm productivity and market valuation and technology investment, such as artificial intelligence, which results in omitted variable (simultaneity) bias. Second, better performance (e.g., more sales and higher market valuation) help firms accumulate extra resources that might result in investing in frontier technologies (artificial intelligence), or worse performing firms might invest more radically in artificial intelligence to catch up with their peers. Both cases cause reverse causation.

To address this issue, I follow two approaches. First I follow early literature (Brynjolfsson and Hitt (2003)) as well as some recent work (Babina et al. (2021)) to take long-differences of the baseline estimation equation as

$$\Delta Y_{i,t+\tau} = \beta_{AI} \times \Delta \text{AI Investment}_{i,t+\tau} + \Delta Controls_{i,t+\tau} + \alpha_j + \alpha_t + \epsilon_{it}.$$

The year differences $\tau = 1, 2, 3, 4, 5$, and industry and year fixed effects are controlled. It absorbs potentially omitted short-term shocks which could be serially correlated with itsself, AI investment, outcome variables, and other controls. Such shocks could diminish in the long-run or simply have opposite forces to cancel each other out.

Second, I follow an instrumental variable approach. I first control for firm fixed effects to absorb time invariant firm attributes, firm specific growth trends and any persistent measurement errors of AI investment, as well as year fixed effects to absorb unobservable aggregate supply and demand shifters. Thus the estimation is based on variations isolated at the firm-year level. Then, I construct an instrumental variable for AI investment from ex-ante industry-level exposure to artificial intelligence technologies and geography-level time-varying exposure to access to data services industry. The IV estimation captures the effects of AI investments over a subgroup of firms, which is similar to the local effects (Angrist and Pischke (2009); Wooldridge (2010)). This approach is valuable as AI investment is skewed and biased towards a small set of distinctive firms (Zolas et al. (2020), and discussions in Section 3.1).

In particular, the instrumental variable is the product of two parts. In the first part, I exploit the Occupational Employment and Wage Statistics (OEWS) database[27] and occupational-level exposure to AI technologies constructed by Felten, Raj, and Seamans (2021)[28], to build ex-ante exposure to AI at industry-level. Specifically, I measure this exposure by calculating the payroll share[29] of high exposure (top quartile) occupations for each industry at 4-digit NAICS level in 2009. I follow Jin and McElheran (2017) and Jin (2022) to construct the second part of IV as the lagged state-year level total payroll[30] in the "Computing Infrastructure Providers, Data Processing, Web Hosting, and Related Services" industry (6-digit NAICS code 518210[31]) weighed by the inverse of price of data storage devices.[32] Thus the IV can be expressed as

$$\text{IV}_{j,s,t} = \frac{\sum_{\tilde{o}} \text{payroll}_{j,\tilde{o},2009}}{\sum_{o} \text{payroll}_{j,o,2009}} \times \left(\frac{\sum_{j=518210} \text{payroll}_{j,s,t}}{\sum_{j} \text{paryoll}_{j,s,t}} \times \frac{1}{P_t}\right)$$

where j represents industry, s represents state, t indicates time, $\tilde{o}$ is the top quartile occupations with AI exposure according to Felten, Raj, and Seamans (2021), and P is the price index of data storage devices.

The broad idea of the construction of the instrument follows a set of previous works that concern the causal impact of technologies, such as AI and robots, on workers and firms. Graetz and Michaels (2018) and Dixon, Hong, and Wu (2021) both use ex-ante industry level exposure to automation technology (robots) derived from occupational tasks that are better performed by robots. Dixon, Hong, and Wu (2021) further interacts the ex-ante exposure measure with the inverse of median price of robots to obtain the time-series dimension of the IV. Similarly, Babina et al. (2021) instruments firm-level AI investments using firms' ex-ante exposure to the supply of AI talents from universities with strong AI research teams. In this paper, I obtain cross-sectional variation of ex-ante industry exposure to AI. To measure this, I exploit the AI exposure measure

[27]The data is publicly avaiable from https://www.bls.gov/oes/tables.htm.

[28]The results are robust with other measures, such as Webb (2019).

[29]The results are robust with using employment share, while payroll share yields larger variation.

[30]The results are robust if the IV is constructed using total employment data.

[31]The definition of this NAICS code is "this industry comprises establishments primarily engaged in providing computing infrastructure, data processing services, Web hosting services (except software publishing), and related services, including streaming support services (except streaming distribution services). Data processing establishments provide complete processing and specialized reports from data supplied by clients or provide automated data processing and data entry services."

[32]Data can be accessed at https://fred.stlouisfed.org/series/PCU334112334112, and the index is aggregated to an annual index.

derived by Felten, Raj, and Seamans (2021), which considers the skills and tasks that are most exposed to the applications of AI at SOC occupation-level. Thus, this ex-ante AI exposure is clearly correlated with AI investment (in human capital) in the following years, and it is likely to be exogenous to the ex-post firm performance since massive investment in AI has not taken off in 2009.

The exposure to data service industry access generates both cross-sectional and time-series variation. It relies on the intensity of the state-level data service industry (NAICS code 518210). This industry contains automated data processing services, cloud computing and storage services, computer storage and data entry services, Infrastructure as a service (IaaS), Platform as a service (PaaS), etc. These services constitute the main exercises and supports to the processing, storage, and management of data, which are vital for the artificial intelligence investment to be effective. Since recent literature has characterized that geographic proximity promotes technology diffusion (Jaffe, Trajtenberg, and Henderson (1993); Thompson and Fox-Kean (2005); Henderson, Jaffe, and Trajtenberg (2005); Singh and Marx (2013); Bai, Jin, and Zhou (2021)) and IT adoption in particular (Bloom et al. (2014); Jin and McElheran (2017); Greenstein and Fang (2020)), firms that are located in data service industry intensive states would be more likely to invest in AI technologies. Thus the state-year level variation in data service intensity satisfies the "relevance assumption". I further adjust this measure by multiplying the inverse of price of data storage devices to take the impact of the advances of data storage technology to access to data into account. Additionally, as Jin and McElheran (2017) and Jin (2022) explain, the state aggregated lagged data service sector intensity is likely to be influence firm performance only through IT labor demand (e.g., cloud computing and AI human capital investment). They argue that these the locations of these data service providers are conditionally exogenous to local AI skill demand based on Armbrust et al. (2009) indicating that the location of data service providers are more efficiency-driven than demand-driven. To further alleviate the concern that the growth of local IT and data sector confounds with both the investment in AI and firm performance, I include the payroll and employment growth in NAICS 518210 of the focal states in all the 2SLS regressions to disentangle the effects of local growth from the IV.

Therefore, the instrumental variable is constructed as the product of logarithm of total counts of H-1B denials at the state-industry-year level and lagged share of total employment of NAICS 518210

at state-year level[33]. As discussed above, both parts of the product are positively correlated with the AI human capital investment. The IV is matched with the Compustat-BGT-EDGAR sample based on the headquarter location of the firms.

4.2 Test of Complementarity

After addressing the estimation and causality of the effect of AI investment in the baseline performance model, I proceed with identifying two sources of complementary firm resources and capabilities to AI: data practices and management practices. I first outline a simple conceptual framework to guide the empirical exercise and derive the regression equation. Then I discuss two formal tests, correlation test and performance test (Brynjolfsson and Milgrom (2013)), to establish complementarities in detail.

4.2.1 Conceptual Framework

In this section, I develop a simple framework to illustrate the complementarities between AI investment and data/management practices, and guide the empirical exercises discussed in Section 4.2.2.

First, firm performance (log total sales, productivity, market value, and Tobin's Q) is modeled as a linear combination[34] of all input factors as follows

$$\pi = a_I + b_I \times D, \tag{2}$$

where π is the performance measure, D denotes the complementary practice (data or management), b_I is the parameter, a_I summarizes all other factors that contributes to the performance π, such as total capital stock, total employment, etc. $a_I, b_I > 0$.[35]

Next, I introduce AI investment into Equation 2. According to the innovation and technology adoption literature (Aghion et al. (2005); Hombert and Matray (2018)), innovation and technology upskilling behavior are risky and incur potential costs, but could potentially raise output and

[33] As an alternative approach, I use the producer price index of computer storage device manufacturing (available from https://fred.stlouisfed.org/series/PCU334112334112) to replace lagged share of data service sector intensity as an aggregate shifter to construct the IV. The results are very robust.

[34] I discuss further about how why this approach is preferred and valid in Appendix Section A.2

[35] The subscripts of firm identifier i and time t are omitted for simplicity.

performance by either increasing the marginal productivity of various capital or reducing costs. The set up of the interplay between AI investment and firm complementary practices is as follows. Each firm chooses a level of investment in artificial intelligence I_{AI} at cost $C(I_{AI}) = \theta + \eta I_{AI} + \frac{1}{2}\mu I_{AI}^2, \theta, \eta, \mu > 0$. The cost consists of three parts which can vary across firms: θ denotes the fixed cost of investment, η stands for the marginal cost, and $\frac{1}{2}\mu I_{AI}^2$ is the quadratic adjustment cost. A firm making higher investment in AI has higher probability to achieve better performance based on its existing assets. Consider a world of two states: the output of performance factors are high or low, that is, $a_I \in \{a_h, a_l\}$ and $b_I \in \{b_h, b_l\}$, $\Delta a = a_h - a_l > 0, \Delta b = b_h - b_l > 0$. The probability that the firm draws a high state of the world should be a function of AI investment, which is modeled as proportional to AI investment with a scalar r: $\mathbb{P}(I = h \mid I_{AI}) = rI_{AI}$.[36]

Hence the expected performance π from Equation 2 can be expressed as

$$\begin{aligned}\mathbb{E}[\pi] &= (a_h + b_h D) rI_{AI} + (a_l + b_l D)(1 - rI_{AI}) - C(I_{AI}) \\ &= (a_l - \theta) + (r\Delta a - \eta) I_{AI} + b_l D + r\Delta b D I_{AI} - \frac{1}{2}\mu I_{AI}^2.\end{aligned}$$

Let $a_l - \theta = \alpha, r\Delta a - \eta = \beta, b_l = \gamma, r\Delta b = \delta$, and skip the higher order moments of AI investment due to the approximation precision of a probability of high order. Then the complmentary performance test regression can be obtained as

$$\pi = \alpha + \beta \times I_{AI} + \gamma \times D + \delta \times I_{AI} \times D. \tag{3}$$

Note that when firms lack complementary practices (e.g., $D = 0$), the impact of I_{AI} is not necessarily positive since the assumption on the sign of $\beta = r\Delta a - \eta$ is not specified. which I also find support to this in the empirical exercises. To develop the relationship between AI investment I_{AI} and its complementary exercises D, I maximize the expected performance $\mathbb{E}[\pi]$ subject to I_{AI} and yield

$$I_{AI}^* = \frac{1}{\mu}(r\Delta b \times D + r\Delta a - \eta). \tag{4}$$

[36]Note that this is consistent with the definition of the AI human capital investment which is the intensity of investment in AI among all investment in labor.

It implies that first, it's only worthwhile to invest in AI ($I_{AI} > 0$) when the firm accumulates enough complementary capital, i.e., $D > (\eta - r\Delta a)/r\Delta b$; second, investment in AI is positively correlated with its complementary exercises D as $\frac{r\Delta b}{\mu} > 0$.

4.2.2 Correlation Test and Performance Gains

Based on Equations 3 and 4 derived from the simple stylized model in Section 4.2.1, I develop formal empirical regressions model as follows.

First, if complementarity exists, according to the testable predictions from Equation 4, one should observe that the existence and higher investment in artificial intelligence takes place among firms with more intensive data and management practices. I test the simple correlations between the complementary factors, as well as after partialling out the specific industry shocks, time trend, and firm fixed effects. I also control for a rich set of firm attributes and decisions, including logarithm of market value, total employment, capital stock, total assets, as well as R&D investments. The regression specification for this correlation test is

$$\text{AI Investment}_{it} = \alpha + \gamma \text{Complementary Practice}_{it} + Controls_{it} + \alpha_i + \alpha_t + \epsilon, \tag{5}$$

where the AI investment, complementary practices (data or management) are defined the same as in regression 1 and Section 3. α_i and α_t are firm and year fixed effects.[37] The correlation test is passed if the coefficient of complementary practices (γ) is positive and significant.

Second, I investigate the coordination problem within the organizations and explore the interaction effects, following Athey and Stern (1998) and Brynjolfsson and Milgrom (2013). The factors are said to be complementary if they reinforce the performance mutually. That is, the impact to performance is strongest when inputs of both factors are raised. Any "mis-coordinated" and "bad-coordinated" practices might yield worse performance (Milgrom and Roberts (1990); Milgrom and Roberts (1995); Brynjolfsson and Milgrom (2013)).[38] The regression for the performance gain test

[37] I use industry fixed effects to replace firm fixed effects in some regression specifications.

[38] More formally, suppose there is a production process $f(x, y)$ that takes two inputs factors x and y. Both x and y are valued either 0 or 1, indicating adoption vs non-adoption, or high intensity vs low intensity. The performance test for complementarity in this case is $\kappa_p \equiv f(1,1)+f(0,0)-f(1,0)-f(0,1) > 0$. Stronger indication of complementarity sometimes argue that $f(1,1) > f(0,0)$, $f(0,0) > f(1,0)$ and $f(0,0) > f(0,1)$. However, the empirical evidence is challenging to find. A saddle shape is more common.

is specified as

$$Y_{it+1} = \alpha + \beta \text{AI Investment}_{it} + \gamma \text{Comp Practice}_{it} + \delta \text{AI Investment}_{it} \times \text{Comp Practice}_{it} + Controls_{it} + \alpha_i + \alpha_t + \epsilon, \quad (6)$$

where the performance variables Y_{it+1}, AI investment, complementary practices (data and management), controls, fixed effects are defined the same as above. The primary coefficient of interest is δ. A positive and significant interaction term coefficient strongly suggests passing the performance test. The sign and significance of the coefficients of AI investment (β) and complementary practices (γ) are ambiguous according to the prediction in Equation 3 and property that "mis- and bad-coordiation" could harm performance. Overall, it is evident to claim complementarity if passing both correlation test ($\gamma > 0$ in regression 5) and performance test ($\delta > 0$ in regression 6).

5 Results

I begin with addressing the impact of AI investment on firm productivity and stock market performance and establishing causality. Then I turn to the empirical tests of identifying complementarities between AI investment and two essential firm resource and capability - data and management practices.

There is limited evidence that AI has strong average effects on firm performance.

To visualize the nonparametric results, Figure 4 plots the bin scatter of TFP (Panel (a)) and Tobin's Q (Panel (b)) on AI investment. The sample is restricted to the firms with positive AI investment, and control variables and year trend are included. In the upper panel, the fitted line is slightly upward trending but not very strong, especially when AI investment is low. The positive association of AI investment and TFP disappears after controlling for firm fixed effects, as also shown in columns (7) and (8) in Table 6. In the bottom panel, I find that AI investment is positively associated with Tobin's Q, and the result is robust with controls and fixed effects, as in column (6) in Table 6.

Furthermore, Table 6 reports the results of average conditional correlation between AI invest-

ment and firm performance, based on regression function 1. I explore firm performance on multiple dimensions: total sales (columns (1)-(2)), market value (columns (3)-(4)), Tobin's Q (columns (5)-(6)), and total factor productivity (columns (7)-(10)).[39] AI investment is positively associated with total sales, market value, and Tobin's Q, but the results on productivity are noisy. The regressions control for key inputs to firm output and valuation beyond AI investment and firm and year fixed effects. The control variables include log of total employment, log of capital stock, R&D expenditure in column (2), (4), and (6). Additionally, capital investment rate is controlled in column (6) as Tobin's Q strongly responds to physical capital expenditure in the Q theory of investment literature. In columns (8) and (10), R&D and capital investment are included and employment and capital stock enter the estimation of the dependent variables (TFP) using simple OLS estimation or the method of Olley and Pakes (1996). I do not find AI investment strongly and significantly correlates with TFP measures on the sample average. Overall, I find limited evidence that AI has strong average effects on firm performance measures on the population of the sample of firms.

The benefits of AI investment become evident following an implementation lag.

The partially alleviate the endogeneity concern and investigate the long-run effects of AI investment, I run long-differences regressions of AI investment on a series of performance variables, including total sales, market valuation, Tobin's Q, and TFP (OLS estimates or Olley and Pakes (1996) estimates). Table 7 shows the coefficients of AI investment in the long-differences regressions where the year differences range from 1 to 5 years. In all performance measures, the effect of AI becomes statistically significant and economically larger in later years than earlier years, which suggests an implementation lag of AI. That is, it takes time for firms to understand how to deploy AI effectively and to put complementary practices in use. Furthermore, Figure 5 visualizes the regression results by plotting and connecting the coefficients of the regressions with confidence intervals. In panel (a), the impact of AI on TFP drops in the second year and bounced back afterwards, which indicates a J-shaped curve and that in the short-run cost of AI could outweigh the benefit. In panel (b), the impact of AI on Tobin's Q is monotonically increasing over years (without J-curve). This might be because that the stock market is forward looking and does not punish firms with short-run costs as long as the potential can be realised.

[39]The definitions of the variables constructed from Compustat can be found in Table A1.

AI has strong impact on firm performance under IV strategy.

Next, I take endogeneity concerns discussed in Section 4.1 into consideration and investigate the causal impact of AI investment on firm sales, productivity, market value and Tobin's Q using instrumental variable in a Two-Stage Least Square (2SLS) estimation. Table 8 displays instrumental variable estimation results.

I run the same regression as in Table 6, but instrument AI investment with the state-industry-year level product of count of H-1B denials and lagged share of total employment of data service industry (NAICS 518210) as discussed in Section 4.1. The first stage of the 2SLS estimation in Table 8 shows that the IV highly correlates with AI investment. The F-Statistic values are all above 23 and the Cragg-Donald Wald F-Statistic values are all above 61, which indicates that the IV avoids the weak instrument curse. The same control variables are included as in Table 6 and additional controls on the local growth of the employment and payroll of the data service industry are also included. Firm fixed effects are included to absorb persistent firm shocks and year fixed effects are included to absorb aggregate demand and supply shocks. Standard errors are clustered at the firm-level to account for any serial correlation in the error terms within firm across years.

The IV coefficients are greater than the OLS coefficients, which reflects the common concern of upward bias due to the sub-sample of firms that invest in AI self-selectively. To address this concern, first, standard OLS estimates could be downward biased due to measurement errors, and the fact that it tries to evaluate the average effects over the entire population of the sample of firms. The majority of the firms (>%50) never invest in AI in the sample and the behavior of AI investment only shifts the performance of a subset of firms. It is likely that the IV estimates captures return to AI investment of a certain sub-sample of firms and these firms enjoy much larger gains from AI investment than their peers. Thus the heterogeneity of the sample population could lead to higher IV estimation coefficients. This is also consistent with the argument that local average treatment effects are usually stronger than the OLS according to Angrist and Pischke (2009) and Wooldridge (2010).[40] Second, investment in GPT (e.g., AI) usually associates with investments on its complementary practices, such as infrastructure, organizational capital, human capital, and other complementary assets. So the IV estimates of return to AI investment could reflect the return

[40]Note that this paper does not argue that the IV estimation is equivalent to the local average treatment effects.

to an aggregate of direct AI investment and indirect investment of AI complements, which leads to larger coefficients.

Specifically, to gauge the magnitude of the effects, I draw mean and standard deviation values of variables from Table 1 and estimation coefficients from columns (6) and (8) in Table 8. A one standard deviation shock (= 2.087 percentage points) to AI investment leads to an increase of 17.3 log points in Tobin's Q, which is almost 34% of the sample mean, and 31% of the standard deviation. Similarly, a one standard deviation shock to AI investment leads to an increase of 19.7 log points of TFP, which is almost two thirds of the sample mean, and 23% the standard deviation. In sum, I find strong and sizable causal effects of AI investment on firm performance in sales, productivity, market value and Tobin's Q.

The complementary firm resources (data practice) and firm capabilities (management practice) are essential to the success of AI investment.

As results in Table 8 demonstrates the causal performance gain from AI investments, I turn to further examining heterogeneity of the impact of AI under the presence of key complementary practices - data and management.

Correlation Tests

Nonparametric correlations are presented in Panel (a) (or (b)) in Figure 6. This figure plots the bin scatter of data practice or management practice against AI investment. Both panels characterize the simple and raw correlations. Data points are grouped into bins and a fitted line is included. The figure shows that majority of data points are clustered at relatively lower AI investment and lower complementary practices region, which is consistent with the data pattern. The bottom panel has fewer data bins because both AI investment and management practice variables include a non trivial amount of zeros. No controls from Table 9 are included when plotting Figure 6, but the results are robust to including them and year indicators.

The strong correlation between investing in AI and data practice (or management practice) can also be verified by Table 9. It shows the regression results of correlation test for complementarity. The first four columns depict the correlation between AI investment and data practice. The estimation in columns (1)-(2) include industry (3-digit NAICS code) fixed effects and year fixed effects. In column (2), firms' market value, employment, capital stock, total asset, and R&D expenditure

rate are included. The correlation coefficient between AI and data practice is smaller in column (2) with the set of controls yet remains strongly significant. I include firm fixed effects in columns (3)-(4) to disentangle changes in data practice and AI investment from persistent trend specific to firms. The correlation becomes smaller and slightly weaker than in the first two columns. That is, more variations are absorbed in more saturated models, but AI investment is still positively and significantly associated with data practice. The next four columns (5)-(8) repeats the exercises, only to replace data practice with management practice. The empirical pattern and implications are similar. Thus, I confirm that both data practice and management practice pass the correlation test with AI investment.

Performance Tests - AI and Data

Following Athey and Stern (1998) and Brynjolfsson and Milgrom (2013), I investigate the second test to identify complementarity. Specifically, I run regression 6 derived in Section 4.2.2 and focus on δ, the coefficient of the interaction term, which reveals to what extent the complementary practices (data and management) heterogeneously improve the returns of AI investment to firm performance. I find clear evidence that the empirical results support the theory predictions.

In Panel (a) Table 10, I present results of complementary effects of AI and data practices on output and productivity. The dependent variables are logarithm of total sales and TFP estimated under simple OLS estimation and Olley and Pakes (1996)[41]. I find that data practice does not contribute much to output (sales) or productivity, however it boosts the impact of AI investment as the coefficient of the interaction term is positive and significant. I also find some evidence that "mis-coordiation" could have an adverse impact on sales or productivity (AI investment coefficients in columns (3)-(4), and data practice coefficients in columns (5)-(6)). It tells that without its complementary factor, a single input could become a burden to the production process. All the results are robust with control variables and firm and year fixed effects. Similarly, in Panel (b) of Table 10, the results on market value and Tobin's Q are presented. As in Panel (a), the complementary effect is clear (strong, positive, and significant interaction effects). Data practice is positively associated with market value and Tobin's Q in all specifications in the table. This is because the data practice measure captures the retrieval, storage, management, and analysis of data-related work within the

[41]The input variables in the OLS estimation are log(employment) and log(capital stock) and output variable is log(sales). The TFP measure is taken as the residual. In Olley and Pakes (1996), the state variable is the log of capital stock, and the proxy variable is the log of capital expenditure.

firm, which turns data into some form of assets that are valued at the stock market.[42]

Figure 7 provides a visualization to the regression results. The upper panel shows the response of TFP to AI investment under high vs low firm data practice. The sample is split into top and bottom quartile of data practice and only positive AI investment firms are included. Control variables in the regressions are included. The bin scatter plot demonstrates a clear divergence while the fitted line under low data practice is downward trending and the fitted line under high data practice is upward trending. The pattern in the bottom panel on Tobin's Q is the same as in Panel (a). These results provide solid support on complementarity (both performance boosting under "good-coordination" and adverse effects under "mis-coordination").

Performance Tests - AI and Management

I replicate the exercises in Table 10 and Figure 7 with management practice to identify another source of complementary factor to AI investment. The interpretation to the results of the interaction effects shown in Table 11 is similar as above. However, I do not find evidence that "mis-coordination" of management practice and AI investment has an impact on firm outcomes. This is probably because management practice is constructed as a human capital resource variable, which has limited effect with the presence of other firm attributes, such as total employment. Figure 8 shows precisely the regression results. The divergence shape is still notable, while the returns to AI investment is flat under low management practice in both TFP and Tobin's Q and is clearly upward sloping under high management practice.[43]

Performance Tests - Marginal Effects of AI Investment under High vs Low Complementary Practices

To summarize the complementary performance test results, I calculate and plot the marginal effects of AI investment on TFP and Tobin's Q. I take coefficients from column (6) under Panel (a) and column (8) under Panel (b) in Table 10, and from column (6) under Panel (a) and column (8) under Panel (b) in Table 11. Based on regression function 6, the marginal effects is specified as

$$\text{Marginal Effects of AI Investment} = \beta + \delta \times \text{Comp Practice}.$$

[42] This result is consistent with Saunders and Tambe (2015).

[43] The figures on other performance variables, total sales and market value, are not presented in the paper. The results are robust.

The high and low value of complementary practices are chosen based on values the sample splits in figures 7 and 8 (one standard deviation above or below the mean within quartile).

Figure 9 plots the point estimate and confidence interval of the marginal effects of AI investments. Notably, the estimates of the marginal effects are statistically different under low vs high data or management practice (p-values listed in the figure). It is striking to observe that the marginal effects are not statistically different from zero if the complementary practices are low. That is, AI investment is never effective without proper stock of complementary practices within the firm. The difference is also sizable. A one standard deviation increase in AI investment (= 2 percentage points) results in 1.4 log points increase in TFP comparing high vs low data practice, and 2.8 log points increase in TFP comparing high vs low management practice as shown in Panel (a) in Figure 9. Similarly, according to Panel (b) in Figure 9, a one standard deviaiton increase in AI investment results in an additional 2.2 log points increase in Tobin's Q for firms with high data practice compared to those with low data practice, and an additional 3.2 log points increase in Tobin's Q for firms with high data practice compared to those with low management practice. Note that these calculations are under the statistics of the average population and the specifications are average effects of the population of the sample.

"Performance Gap"

In the short-run, it shows that under high vs low complementary practices, the "performance gap" in market valuation (Tobin's Q) and TFP is significant and large in magnitude. Next, I examine the "performance gap" in the long-run. As in Figures 10 and 11, not all companies can catch up in the long run, and complementary practices still play an important role in the long-run. I find that firms that invest in complementary practices enjoy long-lasting performance lead and the "performance gap" could persist or even widen.

Overall, these results provide evidence to support the theoretical predictions of complementarities. They also serve as concise practical guidance for the managers considering investing in AI for the organizations.

6 Conclusion

An explosive amount of anecdotal evidence has shown the growth of investment in general purpose technologies, such as artificial intelligence, and its impact on business and society. However, research assessing causal relationships and the complementary factors needed for success is limited to specific industries and anecdotal evidence. In this paper, I establish causality between AI investment and firm performance, and identify two complementary factors - firm resources (data) and firm capabilities (management). Without these two factors, AI fails to contribute to firm production and valuation, like an engine without fuel.

This study contributes to the literature using a large sample of firm characteristic database (Compustat), texts on firm business descriptions (SEC EDGAR), and most importantly, firm-level skill demand data (BGT) enable this study to do these. I find strong and sizable causal local treatment effects of AI on firms' sales, productivity, and market valuations. More importantly, I identify two key complements that drive AI impact and explain why AI is concentrated in a small set of distinctive firms and why AI is not benefiting the population as we expect. That is, it is only worthwhile to adopt AI if the firm accumulates certain amount of data and management practices. Any "mis-coordinated" matches of factors would lead to worse off performance and only the right coordinated pattern (high AI with high data practice or high management practice) can boost firm performance.

Future work could focus on the following topics. First, there is room to improve the measurement. Without the stock of AI (human) capital, it is hard to construct the investment rate of artificial intelligence. Additionally, to the extent of the author's knowledge, there is no granular data on firm-level data practice (decomposed to multiple types of data practices, such as data retrieval, management, and analysis) or management practices (such as KPI measurements, decision centralization, etc.) on a large scale.[44] Second, the causal effects of data and management, the interaction effects, or even the three-way complementarity are interesting to explore. Third, follow-up research could help identify other factors of complementarities that are omitted in this paper.

The results of the paper provide direct evidence that AI has strong and large local treatment

[44]Management and Organizational Practices Survey (MOPS) and World Management Survey (WMS) both concentrate on certain industries.

effects, and a clear picture of complementary effects of data and management practices and AI. These findings contribute to prior work concerning the productivity effects of technology and complementarity in organizations. There are also managerial and policy implications. It is helpful for managers to first evaluate the complementary factors within the organization before making investment in AI, which is usually partially reversible. Society could possibly unlock the potential of enormous productivity gain from AI when developed tandem with its complementary factors, data practices and adequate management practices.

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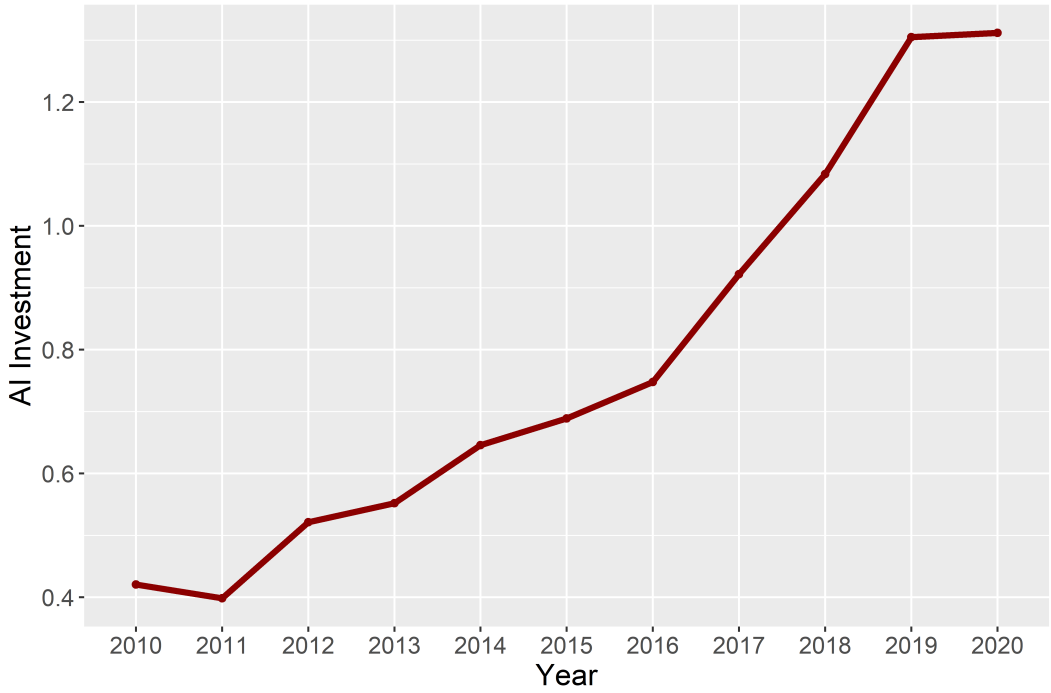
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Figures

Figure 1: Firms' Investment in Artificial Intelligence

(a) AI Investment (Firm Average) Trend



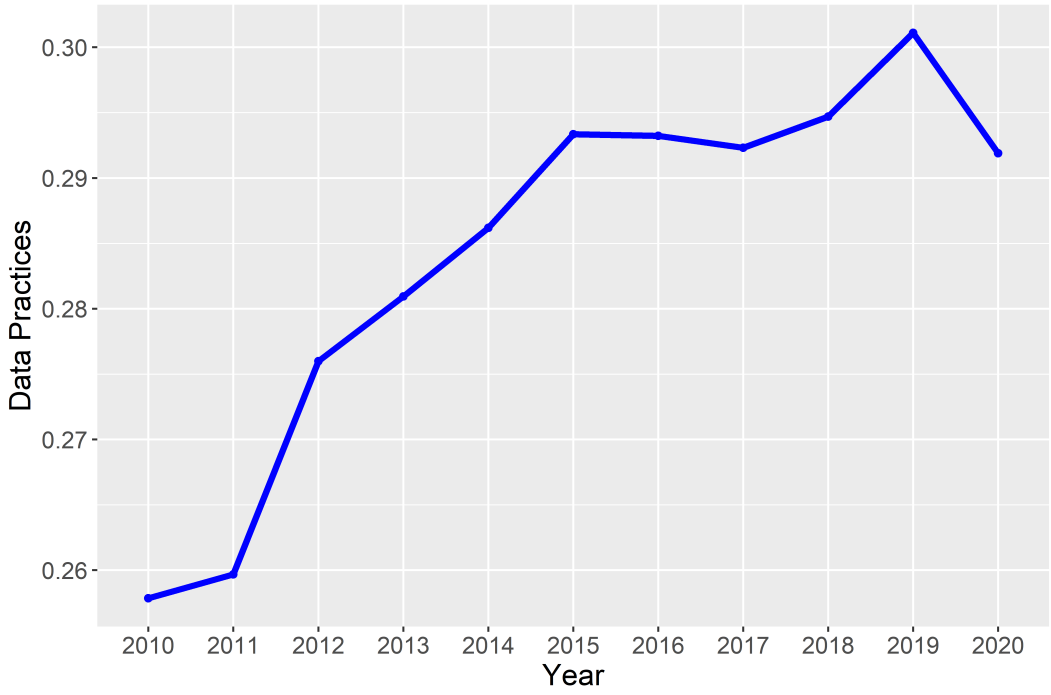
(b) AI Investment (Firm Average) by Sectors



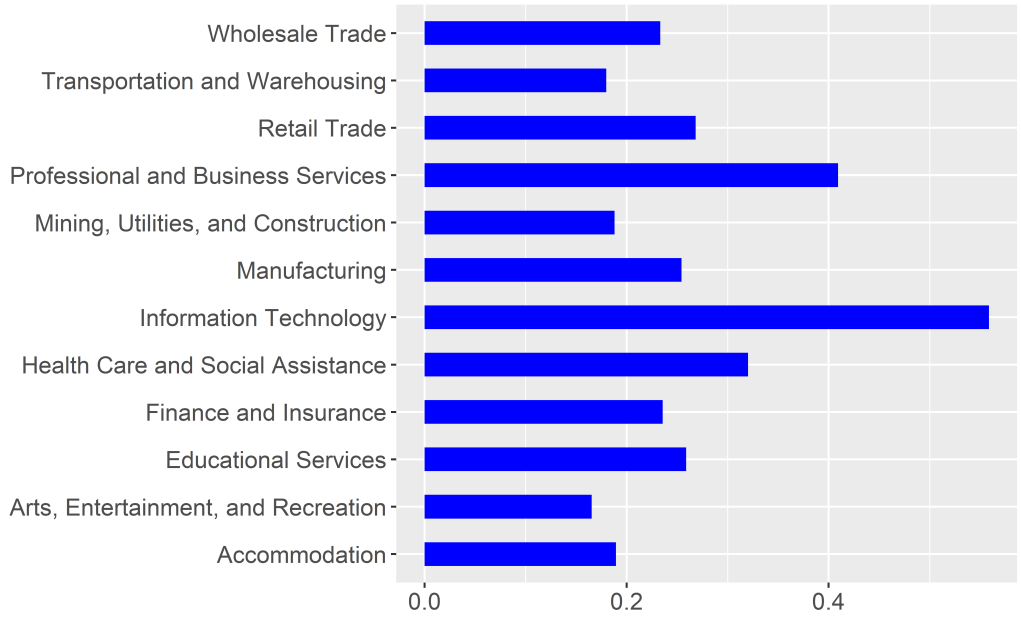
Notes: Compustat-BGT-Edgar matched sample. AI investment (defined in the text) is the average percentage points over firms.

Figure 2: Firms' Data Practices

(a) Data Practices (Firm Average) Trend



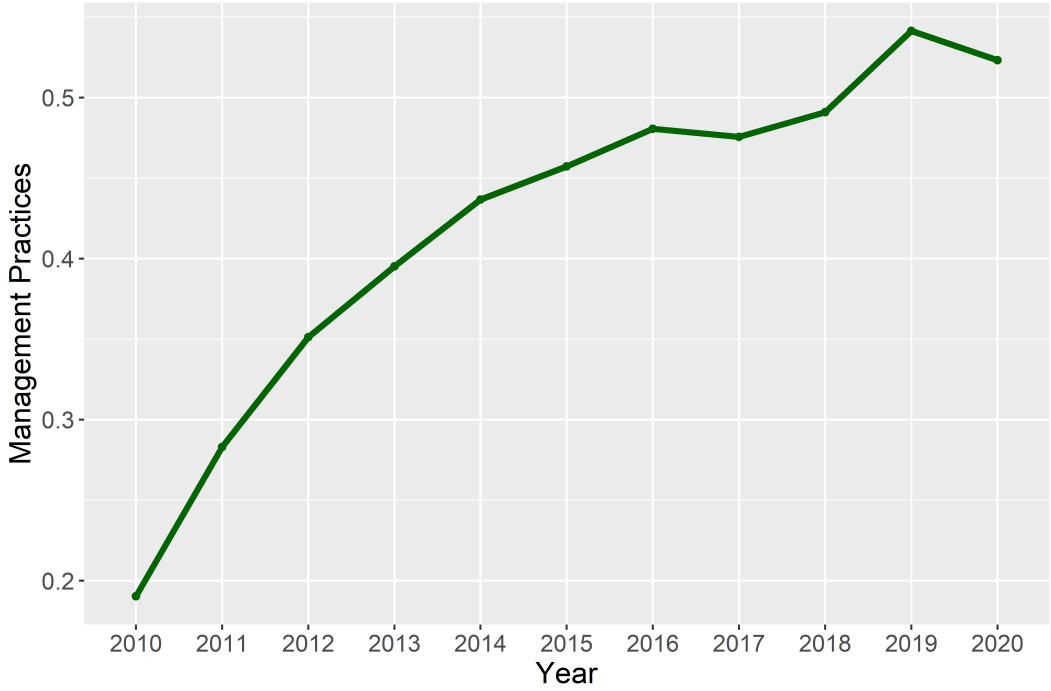
(b) Data Practices (Firm Average) by Sectors



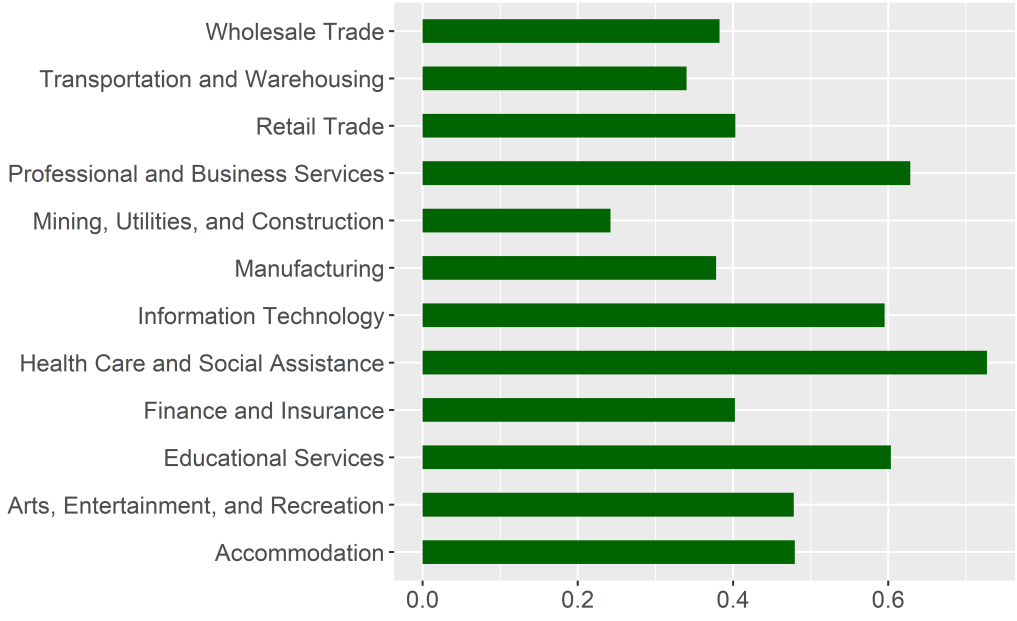
Notes: Compustat-BGT-Edgar matched sample. Data practice (defined in the text) is the average over firms.

Figure 3: Firms' Management Practices

(a) Management Practices (Firm Average) Trend



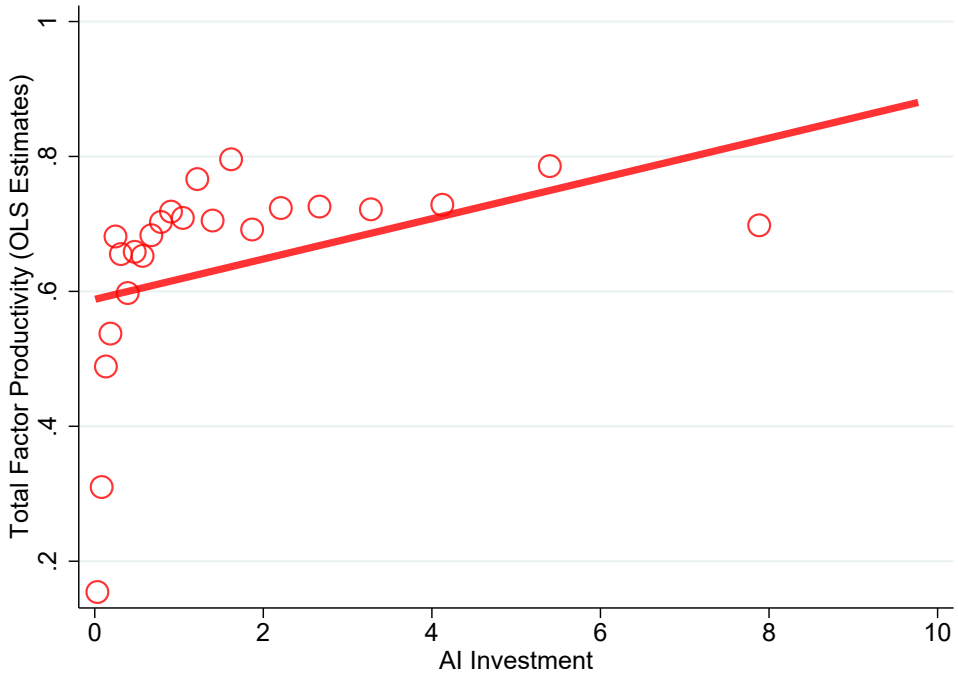
(b) Management Practices (Firm Average) by Sectors



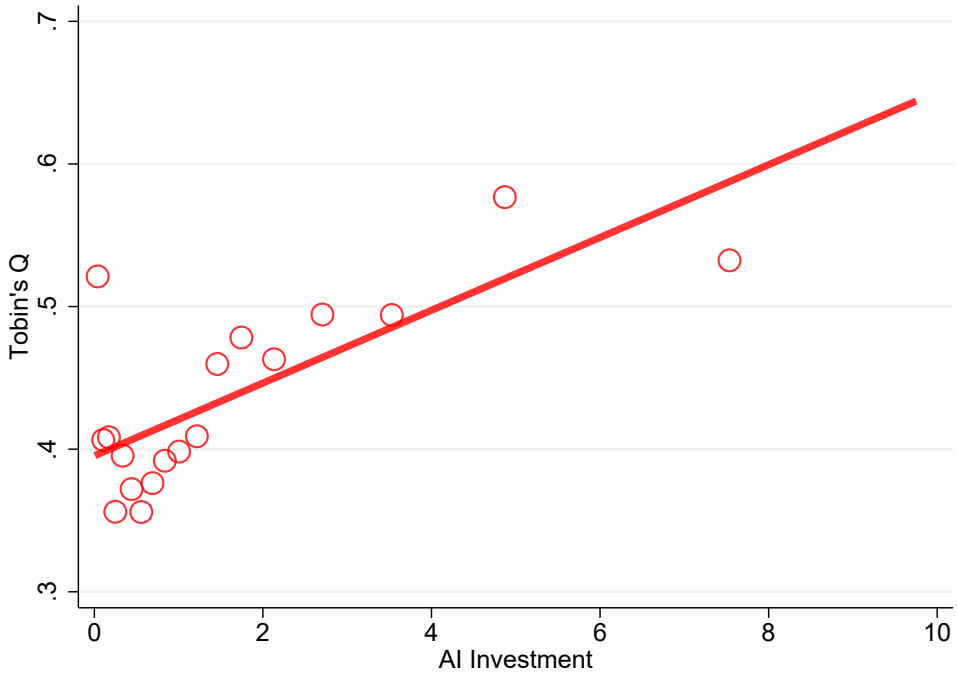
Notes: Compustat-BGT-Edgar matched sample. Management practice (defined in the text) is the average over firms.

Figure 4: Impact of AI Investment on Firm Performance

(a) TFP (OLS Estimates)



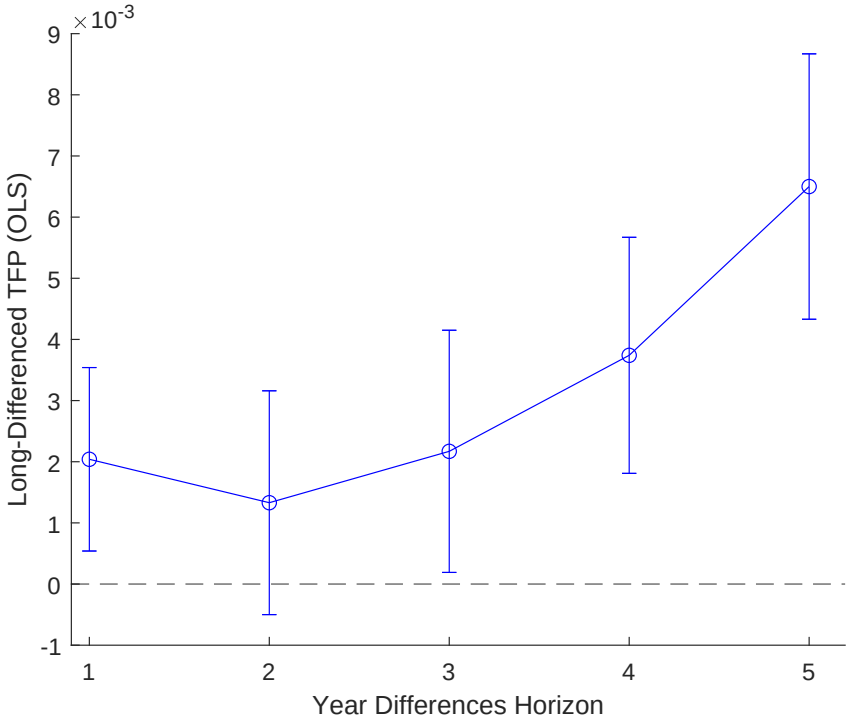
(b) Tobin's Q



Notes: Compustat-BGT-Edgar matched sample with positive AI investment. Bins are optimally selected following Cattaneo et al. (2019). Control variables in the regression tables included.

Figure 5: Long-Differences Results of Impact of AI on Firm Performance

(a) AI Investment on TFP (OLS Estimates)



(b) AI Investment on Tobin's Q

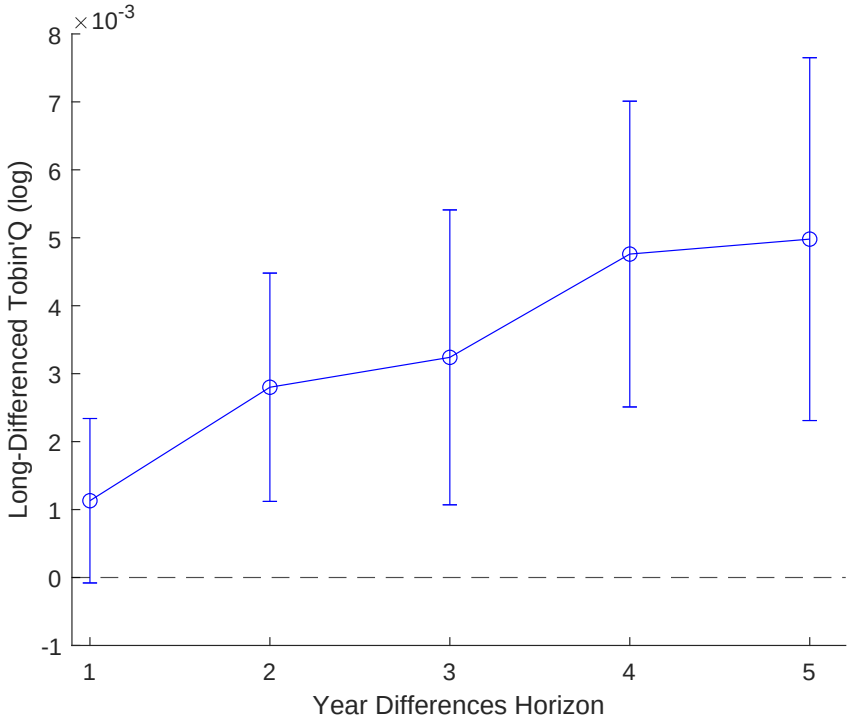
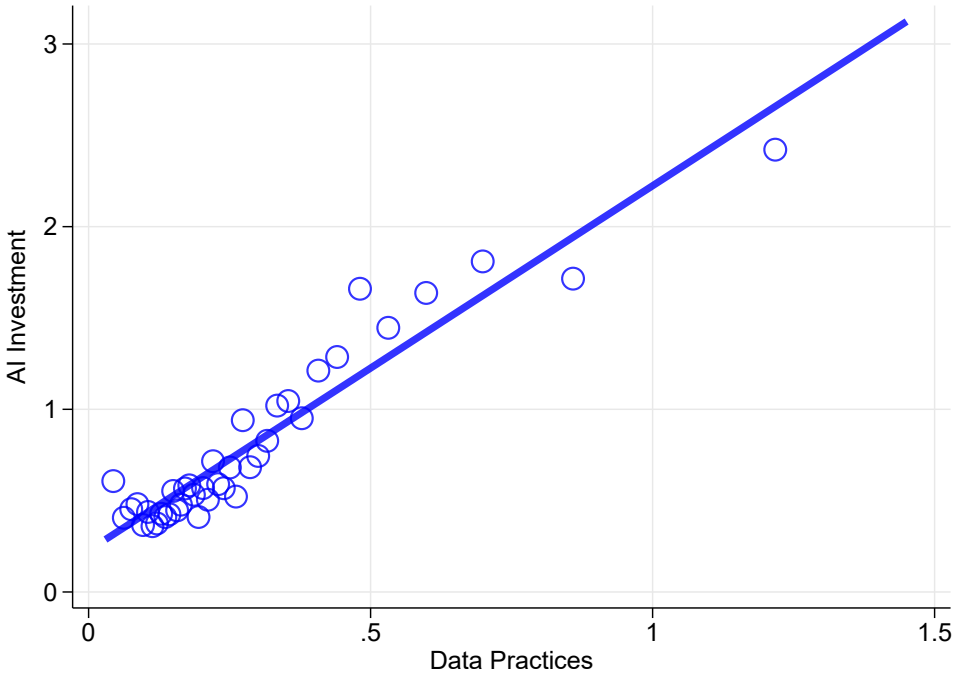
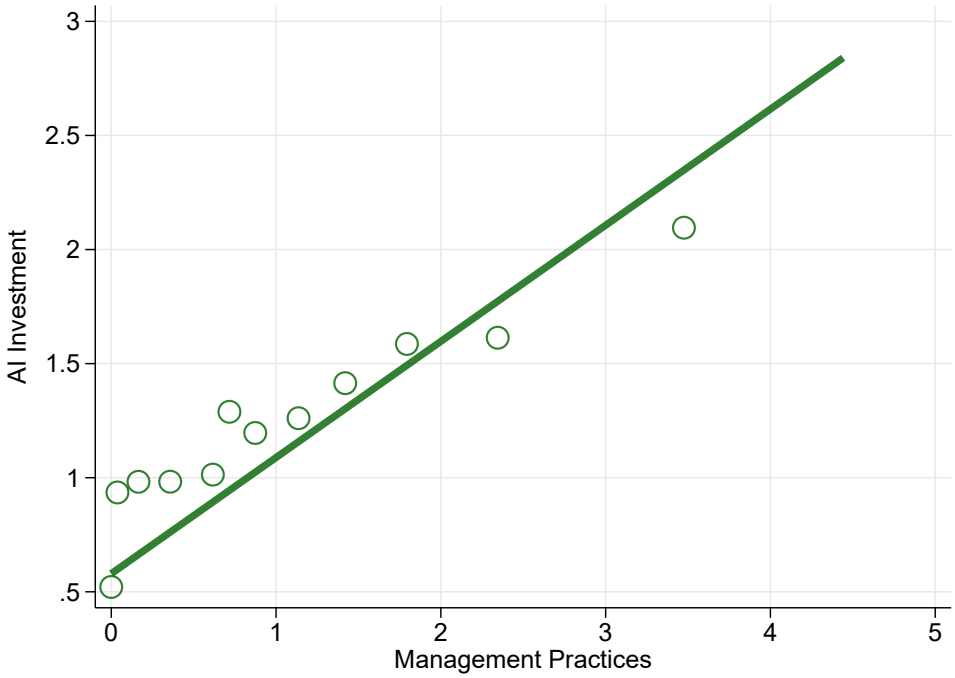


Figure 6: Correlation Test - AI Investment vs Data and Management Practices

(a) AI Investment vs Data Practices



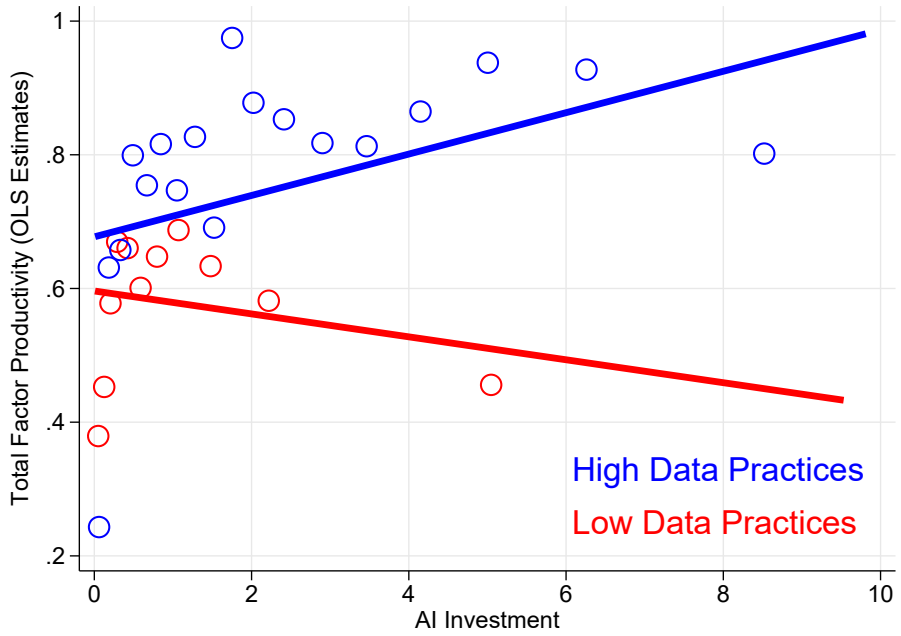
(b) AI Investment vs Management Practices



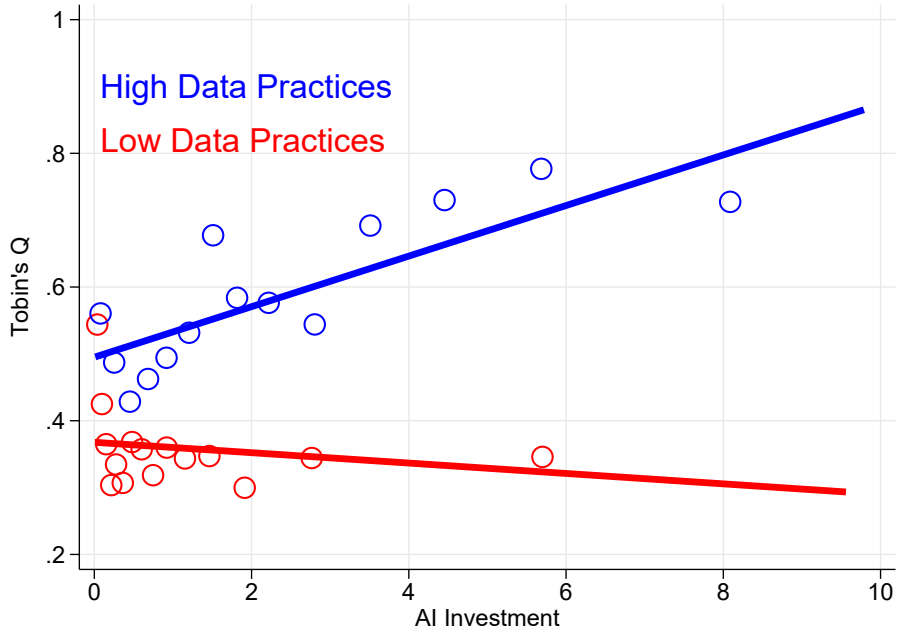
Notes: Compustat-BGT-Edgar matched sample. Bins are optimally selected following Cattaneo et al. (2019). Robust to partialling out controls and year indicators.

Figure 7: Performance Test - AI Investment and Data Practices

(a) Effect of AI Investment on TFP under High vs Low Data Practices



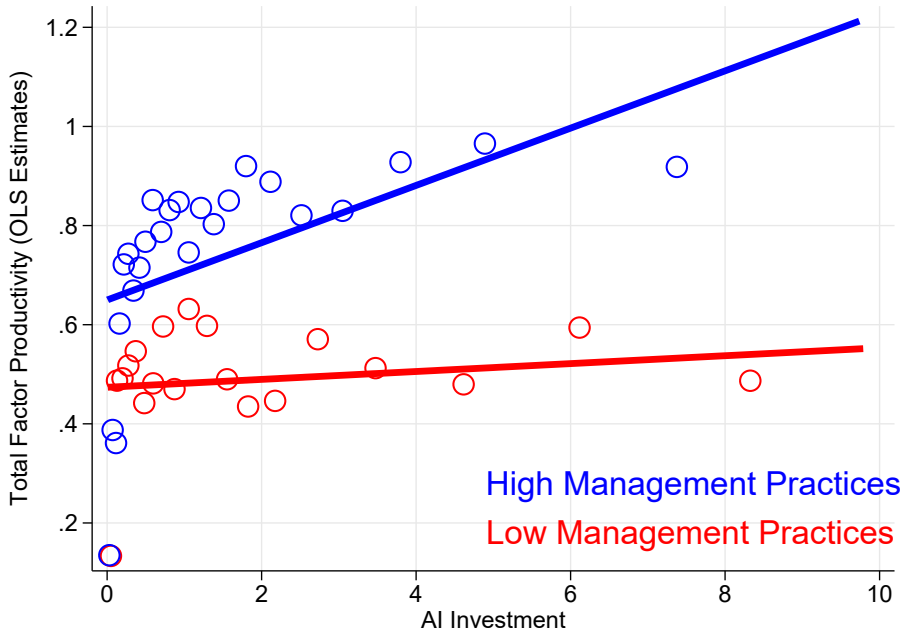
(b) Effect of AI Investment on Tobin's Q under High vs Low Data Practices



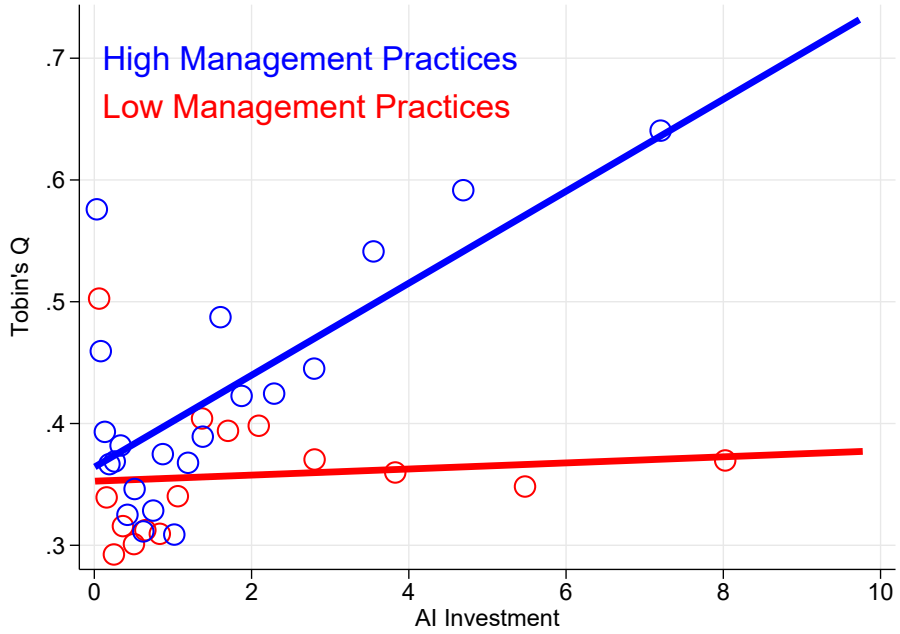
Notes: Compustat-BGT-Edgar matched sample split into high (top quartile) vs low (bottom quartile) data practices with positive AI investment. Bins are optimally selected and linear projections are plotted following Cattaneo et al. (2019). Control variables in the regression tables included.

Figure 8: Performance Test - AI Investment and Management Practices

(a) Effect of AI Investment on TFP under High vs Low Management Practices



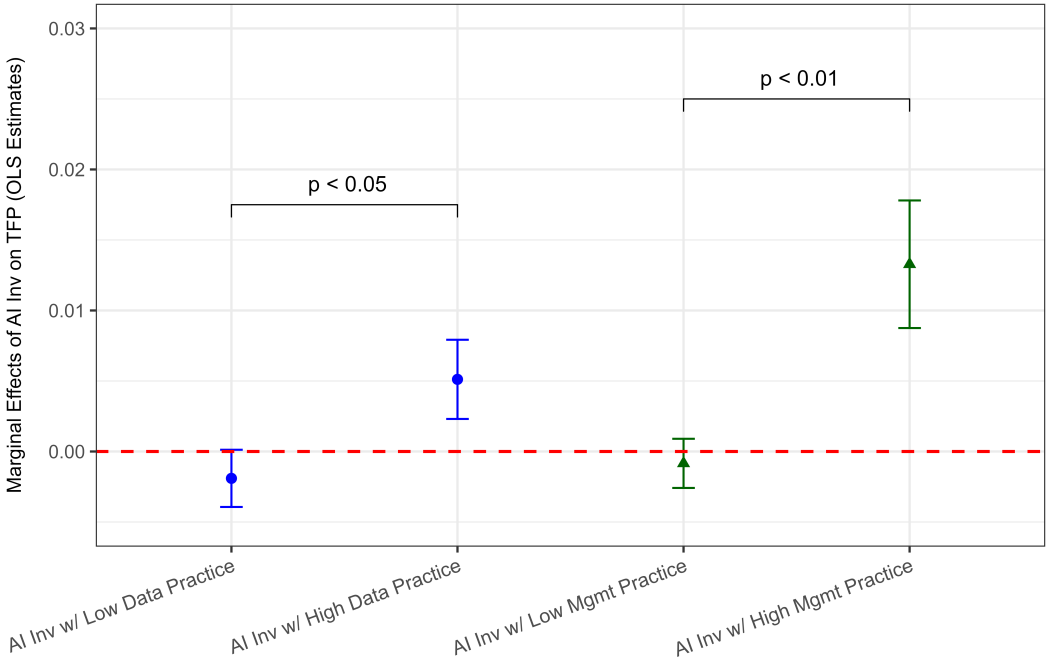
(b) Effect of AI Investment on Tobin's Q under High vs Low Management Practices



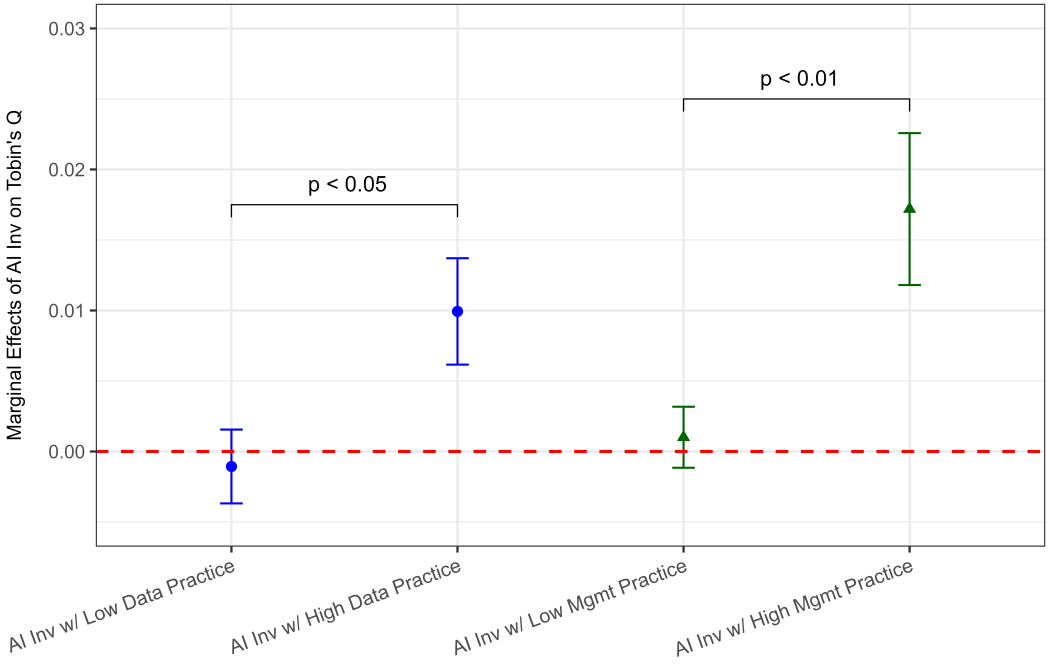
Notes: Compustat-BGT-Edgar matched sample split into high (top quartile) vs low (bottom quartile) management practices with positive AI investment. Bins are optimally selected and linear projections are plotted following Cattaneo et al. (2019). Control variables in the regression tables included.

Figure 9: Margnial Effects of AI Investment

(a) Marginal Effects of AI Investment on TFP



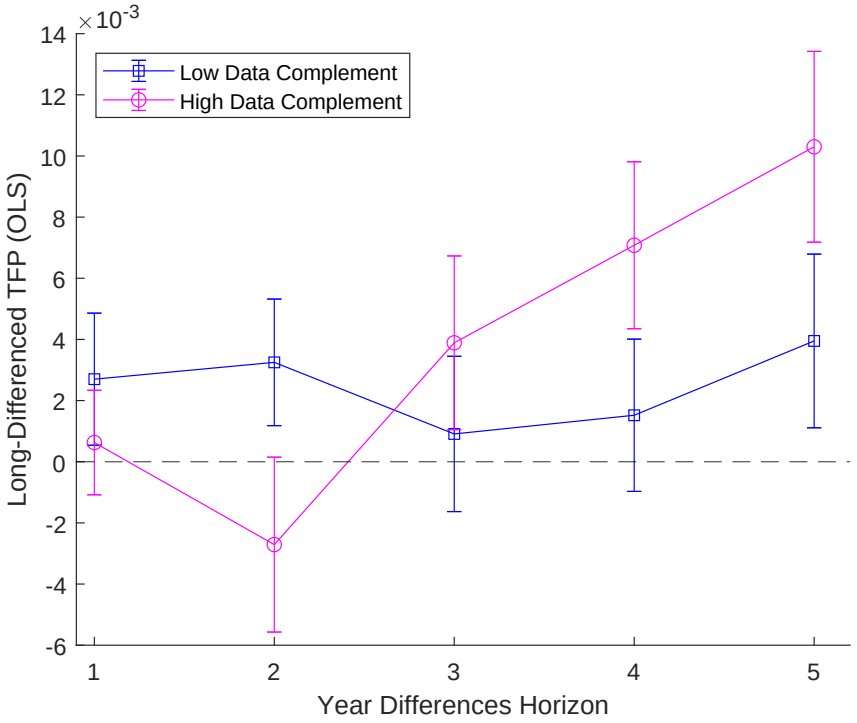
(b) Marginal Effects of AI Investment on Tobin's Q



Notes: This figure reports the marginal effects of AI investment on TFP and Tobin's Q under high vs low data practice or management practice. The results are based on the specification from column (6) under Panel (a) and column (8) under Panel (b) in Table 10, and from column (6) under Panel (a) and column (8) under Panel (b) in Table 11. The split of high vs low data and management practices are defined as mean ± std dev under high vs low sample split in Figures 7 and 8. P-values of t-test between high vs low practices are reported.

Figure 10: Long-Differences of AI Impact on TFP by Sub-samples

(a) High vs Low Data Practices



(b) High vs Low Management Practices

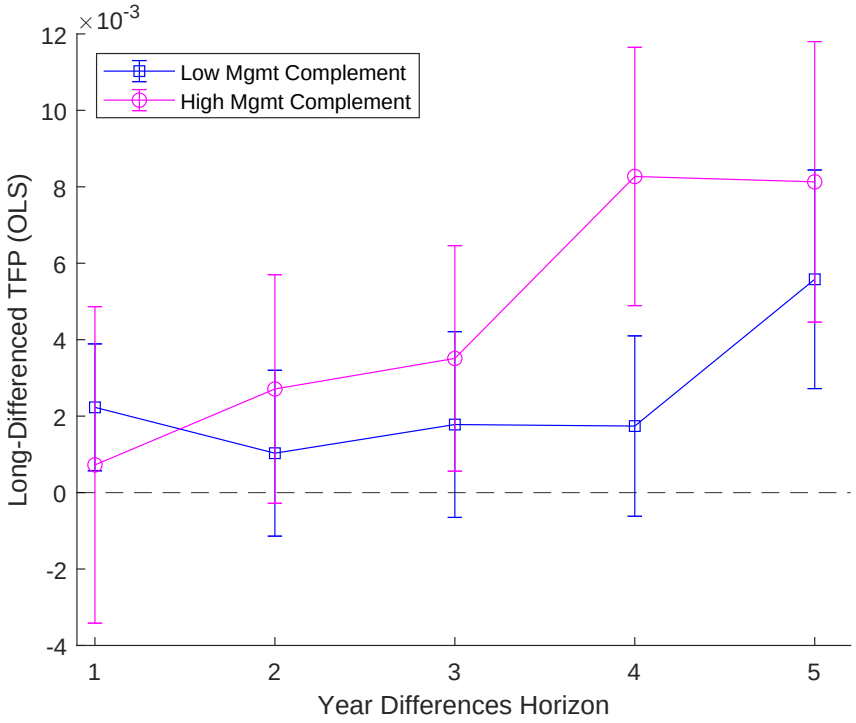
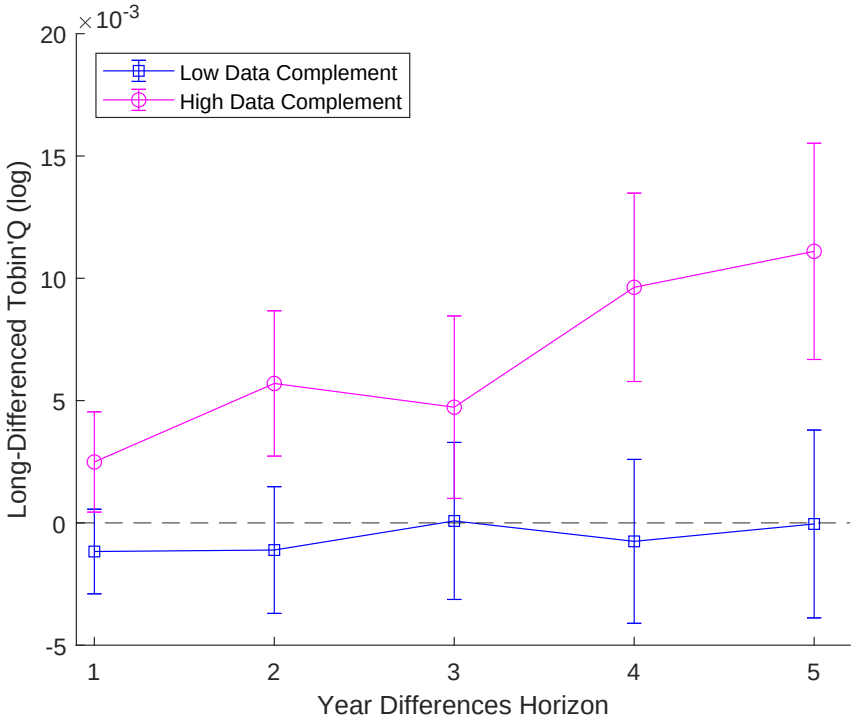
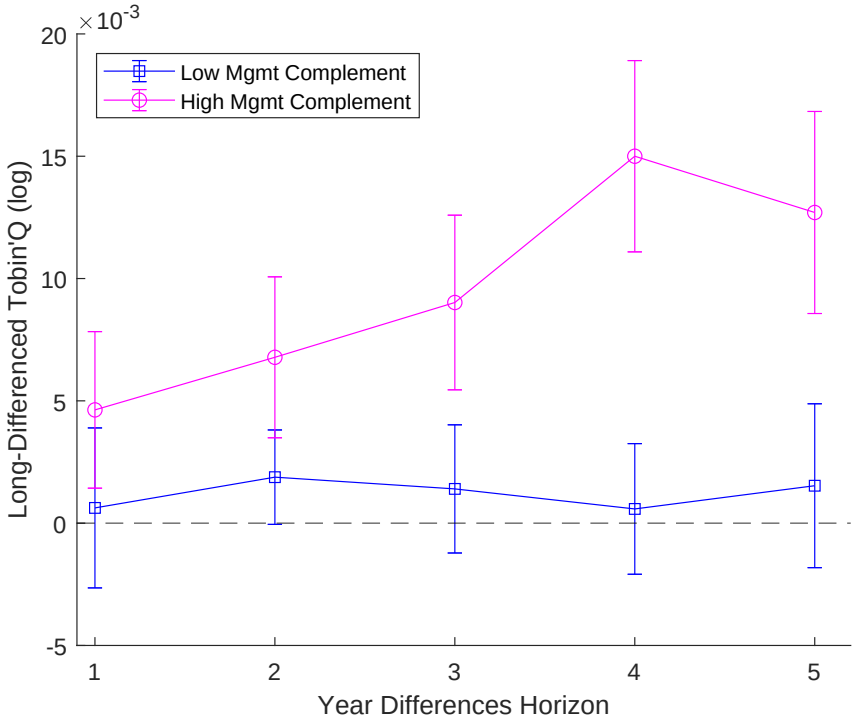


Figure 11: Long-Differences of AI Impact on Tobin's Q by Sub-samples

(a) High vs Low Data Practices



(b) High vs Low Management Practices



Tables

Table 1: Summary Statistics

VARIABLES	(1) Mean	(2) Std Dev	(3) N
AI Investment	0.797	2.087	24,778
Data Practice	0.285	0.232	24,778
Management Practice (Stock)	0.427	0.828	24,778
Management Practice (Share)	0.0364	0.129	24,286
$\log(\text{Market Value})_{t+1}$	7.224	2.158	23,020
$\log(\text{Tobin's Q})_{t+1}$	0.507	0.560	22,988
$\log(\text{Sales})_{t+1}$	6.834	2.084	22,752
$\text{TFP (OLS Estimates)}_{t+1}$	0.300	0.844	20,931
$\text{TFP (OP Estimates)}_{t+1}$	5.468	0.867	20,931
log(Employment)	0.861	2.045	24,286
log(Total Asset)	7.382	2.104	24,770
log(Sales)	6.718	2.111	24,441
log(Market Value)	7.089	2.136	24,778
log(Tobin's Q)	0.505	0.561	24,753
log(Capital Stock)	4.978	2.554	23,515
R&D Investment Rate	0.0368	0.0981	24,778
Investment Rate	0.224	0.175	23,441

Notes: Compustat-BGT-Edgar matched sample. Subscripts are omitted if the variable is at time t.

Table 2: AI and Firm Characteristics

	Dependent Variable: AI Investment							
VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
log(Market Value)	0.103***							0.0797**
	[0.0295]							[0.0329]
log(Employment)		0.108**						-0.0878
		[0.0468]						[0.0659]
log(Capital Stock)			0.127***					0.109**
			[0.0370]					[0.0485]
log(Total Asset)				0.156***				0.0737
				[0.0478]				[0.0712]
R&D Investment					-0.343			-0.0201
					[0.512]			[0.547]
log(Sales)						0.147***		
						[0.0469]		
log(Tobin's Q)							0.217***	
							[0.0803]	
Constant	0.0658	0.710***	0.179	-0.358	0.812***	-0.197	0.690***	-0.751*
	[0.209]	[0.0408]	[0.185]	[0.353]	[0.0188]	[0.316]	[0.0405]	[0.441]
Firm Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	23,057	24,598	24,097	24,247	23,330	24,591	24,573	24,598
R-squared	0.470	0.469	0.470	0.469	0.469	0.469	0.469	0.468
Number of Firms	3090	3270	3205	3209	3126	3269	3267	3270

Notes: Standard errors are clustered at firm level. *** p<0.01, ** p<0.05, * p<0.1. Dependent variable is the AI investment at firm-level. All variables are at time t. All of the regression specifications include firm fixed effects and year fixed effects. Time ranges from 2010 to 2020.

Table 3: List of Data Related Key Phrases (>5000 appearances in SEC Edgar Filings)

access data	data commun	data necessari	data submit	privaci data
addit data	data compani	data network	data substanti	process data
amount data	data compar	data note	data summari	product data
analysi data	data complet	data obtain	data support	proprietari data
analyt data	data consolid	data oper	data system	protect data
applic data	data contain	data percentag	data tabl	provid data
avail data	data continu	data period	data third parti	refer data
base data	data correl	data point	data thousand	relat data
big data	data current	data prepar	data transfer	relev data
breach data	data custom	data present	data trial	report data
busi data	data data	data privaci	data use	result data
certain data	data demonstr	data process	databas	safeti data
claim data	data deriv	data product	develop data	secur data
client data	data determin	data protect	econom data	segment data
clinic data	data develop	data provid	electron data	seismic data
collect data	data driven	data read	engin data	sensit data
compani data	data estim	data receiv	exercis data	servic data
confidenti data	data exist	data regard	flow data	share data
consum data	data expect	data relat	follow data	statist data
cost data	data file	data report	gener data	studi data
critic data	data fiscal	data repres	histor data	support data
custom data	data follow	data requir	includ data	survey data
data addit	data form	data result	increas data	system data
data adjust	data gather	data safeti	industri data	technic data
data analysi	data gener	data secur	inform data	technolog data
data analyt	data histor	data see	integr data	third parti data
data applic	data includ	data segment	interpret data	transact data
data asset	data index	data select	manag data	trial data
data avail	data indic	data servic	market data	unit data
data base	data inform	data set	network data	use data
data breach	data input	data share	new data	user data
data busi	data integr	data show	oper data	util data
data center	data item	data similar	parti data	voic data
data certain	data level	data sourc	patient data	
data chang	data manag	data storag	perform data	
data clinic	data market	data store	person data	
data collect	data measur	data studi	price data	

Notes: This table lists data related unigrams (e.g. databas) and bigrams (hiphen removed, e.g. third-parti) that appears more than 5000 times in the SEC Edgar 10K and 10Q database from 2010 till 2020. All words are stemmed using Porter Stemming Algorithm.

Table 4: Data Practice and Firm Characteristics

	Dependent Variable: Data Practice							
VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
log(Market Value)	0.00662***							0.00937***
	[0.00173]							[0.00192]
log(Employment)		0.00740**						0.00375
		[0.00364]						[0.00498]
log(Capital Stock)			0.00376					0.00450
			[0.00237]					[0.00291]
log(Total Asset)				0.000506				-0.0116**
				[0.00324]				[0.00517]
R&D Investment					0.0590***			0.0539**
					[0.0224]			[0.0222]
log(Sales)						0.00279		
						[0.00296]		
log(Tobin's Q)							0.00981**	
							[0.00404]	
Constant	0.238***	0.281***	0.272***	0.281***	0.283***	0.265***	0.280***	0.283***
	[0.0123]	[0.00317]	[0.0118]	[0.0239]	[0.000820]	[0.0199]	[0.00204]	[0.0312]
Firm Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	23,057	24,598	24,097	24,247	23,330	24,591	24,573	24,598
R-squared	0.898	0.898	0.897	0.900	0.897	0.898	0.898	0.898
Number of Firms	3090	3270	3205	3209	3126	3269	3267	3270

Notes: Standard errors are clustered at firm level. *** p<0.01, ** p<0.05, * p<0.1. Dependent variable is the Data practice at firm-level. All variables are at time t. All of the regression specifications include firm fixed effects and year fixed effects. Time ranges from 2010 to 2020.

Table 5: Management Practice and Firm Characteristics

	Dependent Variable: Management Practice							
VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
log(Market Value)	0.0211***							0.00464
	[0.00761]							[0.00902]
log(Employment)		0.0647***						0.0365**
		[0.0129]						[0.0170]
log(Capital Stock)			0.0470***					0.0300***
			[0.00869]					[0.0106]
log(Total Asset)				0.0495***				0.00498
				[0.0122]				[0.0182]
R&D Investment					0.0923			0.150**
					[0.0628]			[0.0675]
log(Sales)						0.0428***		
						[0.0114]		
log(Tobin's Q)							0.00526	
							[0.0157]	
Constant	0.280***	0.379***	0.204***	0.0645	0.427***	0.147*	0.427***	0.183
	[0.0541]	[0.0113]	[0.0434]	[0.0903]	[0.00230]	[0.0770]	[0.00791]	[0.111]
Firm Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	23,057	24,598	24,097	24,247	23,330	24,591	24,573	24,598
R-squared	0.822	0.821	0.822	0.822	0.821	0.821	0.821	0.821
Number of Firms	3090	3270	3205	3209	3126	3269	3267	3270

Notes: Standard errors are clustered at firm level. *** p<0.01, ** p<0.05, * p<0.1. Dependent variable is the Management practice at firm-level. All variables are at time t. All of the regression specifications include firm fixed effects and year fixed effects. Time ranges from 2010 to 2020.

Table 6: Impact of AI Investment on Firm Performance

	$\log(\text{Sales})_{t+1}$		$\log(\text{Market Value})_{t+1}$		$\log(\text{Tobin's Q})_{t+1}$		TFP (OLS)_{t+1}		TFP (OP)_{t+1}	
VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
AI Investment_t	0.00568**	0.00180	0.00823**	0.00598*	0.00276	0.00379*	0.00151	0.000998	0.00160	0.00108
	[0.00267]	[0.00203]	[0.00374]	[0.00348]	[0.00197]	[0.00204]	[0.00174]	[0.00168]	[0.00175]	[0.00169]
Constant	6.846***	5.732***	7.232***	6.507***	0.504***	0.828***	0.304***	0.327***	5.472***	5.497***
	[0.00209]	[0.0785]	[0.00294]	[0.0871]	[0.00155]	[0.0413]	[0.00138]	[0.00959]	[0.00139]	[0.00959]
Control Variables	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes
Firm Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	22,536	21,172	22,806	21,381	22,775	21,297	20,691	20,566	20,691	20,566
R-squared	0.973	0.984	0.943	0.947	0.833	0.834	0.927	0.928	0.931	0.931
Number of Firms	3073	2905	3124	2946	3122	2943	2885	2870	2885	2870

Notes: Standard errors are clustered at firm level. *** p<0.01, ** p<0.05, * p<0.1. Dependent variables are firm level log of total sales, market value, Tobin's Q, total factor productivity (TFP) estimated using OLS or Olley and Pakes (1996) at time t+1. AI investment is at time t. In columns (2) and (4), control variables log(employment), log(capital stock) and R&D investment rate are included. In column (6), control variables log(employment), log(capital stock), R&D investment rate, and capital investment rate are included to parse out the effects of physical investment on Tobin's Q. In columns (8) and (10), control variables R&D investment rate and capital investment rate are included. All of the regression specifications include firm fixed effects and year fixed effects. Time ranges from 2010 to 2020.

Table 7: Evidence on Long-Differences

Diff in Years	Δlog(Sales) (1)	Δlog(Market Value) (2)	Δlog(Tobin's Q) (3)	ΔTFP (OLS) (4)	ΔTFP (Olley-Pakes) (5)
1	0.00192	0.00203	0.00113	0.00204	0.00216
	[0.00158]	[0.00198]	[0.00121]	[0.00150]	[0.00150]
2	0.00152	0.00484*	0.00280*	0.00133	0.00149
	[0.00190]	[0.00286]	[0.00168]	[0.00183]	[0.00182]
3	0.00276	0.00691**	0.00324	0.00217	0.00239
	[0.00210]	[0.00336]	[0.00217]	[0.00198]	[0.00197]
4	0.00348*	0.00886**	0.00476**	0.00374*	0.00390**
	[0.00202]	[0.00367]	[0.00225]	[0.00193]	[0.00192]
5	0.00612***	0.00941**	0.00498*	0.00659***	0.00680***
	[0.00225]	[0.00444]	[0.00267]	[0.00217]	[0.00216]

Notes: This table presents coefficients of AI investment on firm performance measures (sales, market value, Tobin's Q, TFP) in long-differences regressions. The time frame spans from 1, 2, 3, 4, and 5 years and each coefficient comes from the results of a separate regression. All control variables and time and industry fixed effects are included.

Table 8: Impact of AI Investment on Firm Performance (2SLS IV Estimates)

	$\log(\text{Sales})_{t+1}$		$\log(\text{Market Value})_{t+1}$		$\log(\text{Tobin's Q})_{t+1}$		TFP (OLS)_{t+1}		TFP (OP)_{t+1}	
VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
AI Investment	0.227***	0.125***	0.372***	0.329***	0.0483*	0.0827***	0.0968***	0.0942***	0.102***	0.0992***
	[0.0635]	[0.0410]	[0.0941]	[0.0879]	[0.0290]	[0.0318]	[0.0306]	[0.0307]	[0.0312]	[0.0312]
Control Variables		Yes		Yes		Yes		Yes		Yes
Firm Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Instrumental Variable	1.803***	1.772***	1.847***	1.820***	1.845***	1.838***	1.947***	1.941***	1.947***	1.941***
	[0.356]	[0.368]	[0.356]	[0.369]	[0.356]	[0.370]	[0.371]	[0.373]	[0.371]	[0.373]
First Stage F Statistics	25.67	23.21	26.89	24.36	26.83	24.73	27.48	27.13	27.48	27.13
Cragg-Donald Wald F Stat	69.52	61.22	72.31	63.84	72.09	64.43	73.51	72.04	73.51	72.04
Observations	21,200	19,878	21,448	20,079	21,422	19,998	19,407	19,291	19,407	19,291
Number of Firms	2875	2711	2922	2751	2920	2748	2690	2677	2690	2677

Notes: Standard errors are clustered at firm level. *** p<0.01, ** p<0.05, * p<0.1. This table presents the causal effects of AI investment on firm performance under IV regressions. Dependent variables are firm level log of total sales, market value, Tobin's Q, total factor productivity (TFP) estimated using OLS or Olley and Pakes (1996) at time t+1. AI investment is at time t. In columns (2) and (4), control variables log(employment), log(capital stock) and R&D investment rate are included. In column (6), control variables log(employment), log(capital stock), R&D investment rate, and capital investment rate are included to parse out the effects of physical investment on Tobin's Q. In columns (8) and (10), control variables R&D investment rate and capital investment rate are included. All of the regression specifications include local employment and payroll growth of digital industry (NAICS 521810) at time t-1, firm fixed effects and year fixed effects. First-stage results on the instrument variable are presented, as well as the first stage F-Statistic and Cragg-Donald Wald F-Statistic values. Time ranges from 2010 to 2020.

Table 9: Correlation Test - AI Inv vs Data and Management Practice

	Dependent Variable: AI Investment							
VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Data Practice	1.287***	0.983***	0.433*	0.427*				
	[0.172]	[0.171]	[0.238]	[0.243]				
Management Practice					0.436***	0.332***	0.286***	0.273***
					[0.0379]	[0.0392]	[0.0443]	[0.0453]
Constant	0.430***	-1.433***	0.611***	-1.034***	0.676***	-0.872*	0.676***	-0.801*
	[0.0484]	[0.194]	[0.0236]	[0.189]	[0.0678]	[0.451]	[0.0190]	[0.441]
Control Variables	No	Yes	No	Yes	No	Yes	No	Yes
Industry Fixed Effects	Yes	Yes	No	No	Yes	Yes	No	No
Firm Fixed Effects	No	No	Yes	Yes	No	No	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	24,778	23,246	24,778	23,246	24,598	23,057	24,598	23,057
R-squared	0.095	0.128	0.109	0.133	0.469	0.470	0.471	0.472
Number of Firms	3450	3279	3450	3279	3270	3090	3270	3090

Notes: Standard errors are clustered at firm level. *** p<0.01, ** p<0.05, * p<0.1. Dependent variable is investment in AI human capital at time t. In columns (2), (4), (6) and (8), control variables log(market value), log(employment), log(capital stock), log(total asset), and R&D investment rate are included. Columns (1)-(4) include industry fixed effects. Columns (5)-(8) include firm fixed effects. All of the regression specifications include year fixed effects. Time ranges from 2010 to 2020.

Table 10: Performance Test - AI Investment vs Data Practice

(a) Sales and TFP

	log(Sales)$_{t+1}$				TFP (OLS)$_{t+1}$		TFP (OP)$_{t+1}$	
VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Data Practice$_t$	0.0477	-0.0365	0.00330	-0.0567	-0.0647*	-0.0763**	-0.0622	-0.0747*
	[0.0640]	[0.0419]	[0.0654]	[0.0424]	[0.0380]	[0.0387]	[0.0383]	[0.0389]
AI Investment$_t$			-0.00860**	-0.00476*		-0.00252		-0.00271
			[0.00355]	[0.00260]		[0.00222]		[0.00221]
Data Practice$_t$ ×			0.0361***	0.0163***		0.00891**		0.00961**
AI Investment$_t$			[0.00804]	[0.00503]		[0.00437]		[0.00438]
Constant	6.837***	5.742***	6.845***	5.749***	0.346***	0.348***	5.516***	5.518***
	[0.0180]	[0.0813]	[0.0184]	[0.0814]	[0.0143]	[0.0144]	[0.0144]	[0.0145]
Control Variables	No	Yes	No	Yes	No	Yes	No	Yes
Firm Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	22,536	21,172	22,536	21,172	20,566	20,566	20,566	20,566
R-squared	0.973	0.984	0.973	0.984	0.928	0.928	0.931	0.931
Number of Firms	3073	2905	3073	2905	2870	2870	2870	2870

Notes: Standard errors are clustered at firm level. *** p<0.01, ** p<0.05, * p<0.1. Dependent variables are firm level log of total sales and total factor productivity (TFP) estimated using OLS or Olley and Pakes (1996) at time t+1. The independent variables include AI investment, data practice and their interaction at time t. In columns (2) and (4), control variables log(employment), log(capital stock) and R&D investment rate are included. In columns (8) and (10), control variables R&D investment rate and capital investment rate are included to parse out the effects of physical investment on Tobin's Q. All of the regression specifications include firm fixed effects and year fixed effects. Time ranges from 2010 to 2020.

Table 10: Performance Test - AI Investment vs Data Practice

(b) Market Value and Tobin's Q

	log(Market Value)$_{t+1}$				log(Tobin's Q)$_{t+1}$			
VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Data Practice$_t$	0.238***	0.218***	0.183**	0.180**	0.0894**	0.0928**	0.0759*	0.0745*
	[0.0876]	[0.0822]	[0.0893]	[0.0835]	[0.0400]	[0.0412]	[0.0402]	[0.0414]
AI Investment$_t$			-0.00976*	-0.00612			-0.00156	-0.00202
			[0.00559]	[0.00534]			[0.00276]	[0.00292]
Data Practice$_t$ ×			0.0445***	0.0290***			0.0106*	0.0140**
AI Investment$_t$			[0.0110]	[0.0102]			[0.00607]	[0.00628]
Constant	7.171***	6.449***	7.180***	6.461***	0.481***	0.804***	0.482***	0.809***
	[0.0247]	[0.0896]	[0.0253]	[0.0899]	[0.0113]	[0.0426]	[0.0116]	[0.0426]
Control Variables	No	Yes	No	Yes	No	Yes	No	Yes
Firm Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	22,806	21,381	22,806	21,381	22,775	21,297	22,775	21,297
R-squared	0.943	0.947	0.943	0.947	0.833	0.834	0.833	0.835
Number of Firms	3124	2946	3124	2946	3122	2943	3122	2943

Notes: Standard errors are clustered at firm level. *** p<0.01, ** p<0.05, * p<0.1. Dependent variables are firm level log of market value and Tobin's Q at time t+1. The independent variables include AI investment, data practice and their interaction at time t. In columns (2) and (4), control variables log(employment), log(capital stock) and R&D investment rate are included. In columns (8) and (10), control variables R&D investment rate and capital investment rate are included. All of the regression specifications include firm fixed effects and year fixed effects. Time ranges from 2010 to 2020.

Table 11: Performance Test - AI Investment vs Management Practice

(a) Sales and TFP

	$\log(\text{Sales})_{t+1}$				TFP $(\text{OLS})_{t+1}$		TFP $(\text{OP})_{t+1}$	
VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Mgmt Practice$_t$	0.0266**	0.00674	0.0137	-0.00251	-0.0328	-0.103	-0.0321	-0.106
	[0.0113]	[0.00906]	[0.0114]	[0.00925]	[0.0727]	[0.0813]	[0.0737]	[0.0819]
AI Investment$_t$			0.00272	-0.000307		-0.000842		-0.000853
			[0.00293]	[0.00258]		[0.00174]		[0.00176]
Mgmt Practice$_t$ ×			0.00583**	0.00446**		0.0383***		0.0401***
AI Investment$_t$			[0.00294]	[0.00220]		[0.0128]		[0.0130]
Constant	6.839***	5.052***	6.838***	5.056***	0.328***	0.329***	5.499***	5.499***
	[0.00502]	[0.0893]	[0.00529]	[0.0894]	[0.00963]	[0.00958]	[0.00963]	[0.00957]
Control Variables	No	Yes	No	Yes	No	Yes	No	Yes
Firm Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	22,536	21,395	22,536	21,395	20,526	20,526	20,526	20,526
R-squared	0.973	0.980	0.973	0.980	0.928	0.928	0.931	0.932
Number of Firms	3073	2935	3073	2935	2866	2866	2866	2866

Notes: Standard errors are clustered at firm level. *** p<0.01, ** p<0.05, * p<0.1. Dependent variables are firm level log of total sales and total factor productivity (TFP) estimated using OLS or Olley and Pakes (1996) at time t+1. The independent variables include AI investment, management practice and their interaction at time t. In columns (2) and (4), control variables log(capital stock) and R&D investment rate are included. log(employment) is not controlled since management practice is measured as the stock of certain human capital, which is a component of total employment. In columns (8) and (10), control variables R&D investment rate and capital investment rate are included. I use share of management human capital investment to total job postings as management practice measure in columns (5)-(8) since TFP are estimated by partialling out total employment stock. All of the regression specifications include firm fixed effects and year fixed effects. Time ranges from 2010 to 2020.

Table 11: Performance Test - AI Investment vs Management Practice

(b) Market Value and Tobin's Q

	log(Market Value)$_{t+1}$				log(Tobin's Q)$_{t+1}$			
VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Mgmt Practice$_t$	0.0250	0.000753	0.00520	-0.0147	-0.000386	0.00443	-0.0126*	-0.00927
	[0.0181]	[0.0171]	[0.0197]	[0.0187]	[0.00706]	[0.00723]	[0.00742]	[0.00768]
AI Investment$_t$			0.00405	0.00303			0.000300	0.00101
			[0.00410]	[0.00382]			[0.00209]	[0.00216]
Mgmt Practice$_t$ ×			0.00895**	0.00696**			0.00582***	0.00639***
AI Investment$_t$			[0.00353]	[0.00350]			[0.00224]	[0.00229]
Constant	7.228***	6.507***	7.227***	6.511***	0.506***	0.827***	0.507***	0.831***
	[0.00795]	[0.0875]	[0.00857]	[0.0875]	[0.00309]	[0.0414]	[0.00331]	[0.0415]
Control Variables	No	Yes	No	Yes	No	Yes	No	Yes
Firm Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	22,806	21,381	22,806	21,381	22,775	21,297	22,775	21,297
R-squared	0.943	0.947	0.943	0.947	0.833	0.834	0.833	0.835
Number of Firms	3124	2946	3124	2946	3122	2943	3122	2943

Notes: Standard errors are clustered at firm level. *** p<0.01, ** p<0.05, * p<0.1. Dependent variables are firm level log of total sales and total factor productivity (TFP) estimated using OLS or Olley and Pakes (1996) at time t+1. The independent variables include AI investment, management practice and their interaction at time t. In columns (2) and (4), control variables log(employment), log(capital stock) and R&D investment rate are included. In columns (8) and (10), control variables R&D investment rate and capital investment rate are included to parse out the effects of physical investment on Tobin's Q. All of the regression specifications include firm fixed effects and year fixed effects. Time ranges from 2010 to 2020.

A Appendix

A.1 Data Appendix

Table A1: Definition of Varibles

log(Market Value)	The log of common shares outstanding ($csho$) $\times$ price closed at fiscal year ($prcc_f$).
log(Tobin's Q)	Tobin's Q $= \frac{\text{Market Value+Market Value of Liability}}{\text{Total Asset Value}} = \frac{csho \times prcc_f + at - ceq}{at}$. Market value of liability is assumed to be approximately equal to the book value of liability. The log of Tobin's Q.
log(Sales)	The log of total sales ($sale$).
TFP (OLS Estimates)	Estimated total factor productivity through OLS regressions, controlling for firm and year fixed effects. The input variables are log of total employment (emp) and log of capital stock ($ppent$).
TFP (OP Estimates)	Estimated total factor productivity through Olley and Pakes (1996) methods. The state variable is the log of capital stock ($ppent$), and the proxy variable is the log of capital expenditure ($capx$).
log(Employment)	The log of total employment (emp).
log(Total Asset)	The log of total asset (at).
log(Capital Stock)	The log of total stock of property, plant and equipment ($ppent$).
R&D Investment Rate	The ratio of R&D expenditure and total asset (xrd/at). Missings are replaced with zero.
Investment Rate	The ratio of capital expenditure and capital stock ($capx/ppent$).

A.2 Conceptual Framework

In this section, I discuss firm performance measures, such as sales, productivity, market valuation, and Tobin's Q can be represented in the linear form in Section 4.2.1.

First, sales and TFP can be studied by looking at the Cobb-Douglas production function. Suppose that firm production function is given in

$$Y_{it} = A_{it} K_{it}^{\alpha_K} L_{it}^{\alpha_L} e^{\alpha_D D_{it}},$$

where Y_{it} is the total sales of firm i in year t, A_{it} is the firm specific total factor productivity, K_{it} and L_{it} denote firm's capital stock and employment, D_{it} represents the complementary practice, such as data or management, α's are parameters. The Cobb-Douglas production function can be log linearized[45] into

$$y_{it} = a_{it} + \alpha_K k_{it} + \alpha_L l_{it} + \alpha_D D_{it}. \tag{7}$$

Thus both sales and TFP can be shown as a linear combination of complementary practice (D_{it}) and other factors.

Second, the derivation of market value and Tobin's Q equation is based upon prior work, which writes market value of firms into the sum of of tangible and intangible assets (Hall (2001); Brynjolfsson, Hitt, and Yang (2002); Saunders and Tambe (2015); Tambe et al. (2020)):

$$MV_{it} = TA_{it} + IA_{it},$$

where MV_{it} is the market value of firm i in year t, TA_{it} and IA_{it} are the replacement value of tangible assets and value of intangible assets respectively. The value of tangible assets is the sum of all of firm's N tangible assets, written as $TA_{it} = \sum_{n=1}^{N} \beta_n TA_{int}$. Similarly, the value of intangible assets is the sum of all of firm's M intangible assets, written as $IA_{it} = \sum_{m=1}^{M-1} \gamma_m IA_{imt} + D_{it}$, where the complementary practice (data or management) is isolated. Thus, the market value can be written as

$$MV_{it} = \sum_{n=1}^{N} \beta_n TA_{int} + \sum_{m=1}^{M-1} \gamma_m IA_{imt} + D_{it}. \tag{8}$$

Under the assumptions in Hall (2001), the marginal Tobin's Q equals the average Tobin's Q, which is

$$q_{it} = \frac{MV_{it}}{TA_{it}} = 1 + \frac{IA_{it}}{TA_{it}}, \tag{9}$$

$$= 1 + \sum_{m=1}^{M-1} \zeta_m \frac{IA_{imt}}{TA_{it}} + D_{it}, \tag{10}$$

[45] Small cases represent the logarithm form of the upper case variables.

Similar to Equation 7, Equations 8 and 10 indicate that market value and Tobin's Q can also be represented as a linear combination of complementary practice and other factors.