Artificial Intelligence and Mergers and Acquisitions

Abstract

Using detailed data on employees' job skills, this study examines the relationship between firms' artificial intelligence (AI) capabilities and mergers and acquisitions (M&As). Our findings indicate that firms with higher concentrations of AI talent (high-AI firms) achieve superior acquisition performance during announcement periods. Further analysis shows that this superior performance is more pronounced among acquisitions of data-intensive targets. We then test whether firms leverage the strategic complementarity between AI expertise and data resources, and find that high-AI firms are significantly more likely to merge with data-intensive firms and actively hire data analytics specialists. Moreover, mergers with high-AI acquirers and data-intensive targets experience increased filings and citations of AI-related patents, suggesting better innovation capabilities in the post-merger period. Our results are robust to an instrumental variable approach and are not explained by higher post-merger mobility of AI-skilled employees or better pre-merger fundamentals of acquirers. By identifying AI-data synergy as a key driver of value creation in M&As, this research sheds light on how technological advancements are reshaping firm boundaries.

Keywords: Mergers and Acquisitions, Artificial Intelligence, Data Assets, Human Capital, Innovation

1. Introduction

As a cornerstone of modern technological advancement, AI is revolutionizing business by enabling firms to enhance workforce capabilities, analyze vast datasets, and automate complex processes. Firms that excel in AI adoption demonstrate superior growth and innovation (Babina, Fedyk, He, and Hodson, 2024). These advantages have made AI an influencing factor for corporate decision-making (Agrawal, Gans, and Goldfarb, 2019). As AI continues to evolve, its capacity to reshape firm boundaries has become a compelling question for researchers and practitioners. On one hand, AI enables firms to handle complex processes more efficiently, extending their operational reach (Acemoglu and Restrepo, 2019). On the other hand, the rise of AI fuels a growing appetite for sophisticated data processing infrastructure and perhaps more importantly, for large, specialized datasets (Cockburn, Henderson, and Stern, 2018; Beraja, Yang, and Yuchtman, 2023). This forces firms to prioritize the accumulation of data, first from internal reserves, and, if necessary, from external sources. These factors collectively expand the scope for profit creation and redefine firm boundaries.

Mergers and acquisitions (M&As) are pivotal events in redefining firm boundaries, providing an ideal context to examine the relationship between corporate AI capabilities and firm boundaries. In this study, we gauge firms' AI capabilities using a dataset on employee skills posted by individuals on a large job-hunting platform from 2009 to 2019. We quantify firms' AI capabilities based on the AI skills possessed by firms' employees. We then investigate the effect of acquirers' AI capabilities on their M&A performance, measured by the cumulative abnormal return (CAR) for each acquisition announcement.

Our findings reveal that announcement-period CARs are positively associated with acquirers' AI capabilities, suggesting superior acquisition performance by firms with greater AI capabilities compared to other firms. To address endogeneity, we employ an instrumental variable approach, using the share of AI graduates from nearby universities as an instrument for acquirers' AI capabilities. The corresponding two-stage least squares (2SLS) estimates consistently show a significantly positive effect of acquirers' AI capabilities on announcement returns.

We next explore the source of value creation by AI in M&As. We find evidence consistent with the strategic alignment between AI expertise and data assets. More specifically, subsample analysis show that the superior returns of high-AI acquirers are concentrated among acquisitions targeting data-rich firms. Economically, a one-standard-deviation increase in our AI capability measure leads to a 1.76% increase in CARs for acquisitions of data-intensive targets. In addition, tests that incorporate interactions between acquirer and target characteristics confirm that acquisitions involving high-AI acquirers and data-intensive targets outperform all other acquisition types. In contrast, acquisitions involving either high-AI acquirers and data-poor targets or low-AI acquirers and data-intensive targets yield poorer outcomes. These findings imply the synergies between AI expertise and substantial data resources.

To further validate that AI-data synergy motivates firms' acquisitions, we conduct two sets of tests. First, we analyze hiring trends prior to acquisitions. Our findings show that high-AI firms recruit more data analytics specialists than industry peers leading up to acquisitions, while low-AI firms show a declining trend in such hiring. Additionally, high-AI firms hire more individuals with combined expertise in AI and data analytics, further emphasizing their commitment to leveraging AI-data complementarity. In the second set of tests, following Bena and Li (2014), we create a sample of potential merger pairs. Using a conditional logit model, we find that acquirers with higher AI capabilities and targets with substantial data assets are more likely to form merger pairs. This finding further supports the notion that the complementarity between AI capabilities and data assets drives M&As.

Next, a critical aspect of our study is understanding the specific benefits AI can create when integrated with data assets. Prior research highlights AI's potential to drive innovation by leveraging large datasets to uncover new opportunities and develop cutting-edge technologies (Cockburn, Henderson, and Stern, 2018). To investigate whether these potential benefits materialize by combining AI with data, we examine the post-merger innovation outcomes of the merged firms. Our findings indicate that high-AI acquirers targeting data-rich firms experience significant increases in patent filings and citations during the post-merger period. We also find that such mergers experience a surge in filings and citations of AI patents, a type of innovation that is particularly reliant on data resources (Beraja, Yang, and Yuchtman, 2023). This suggests that the integration of AI and data catalyzes innovation, fostering long-term value creation.

An alternative explanation is that the transferability of AI skills across firms might create spillover effects, improving the performance of target firms and, ultimately, the merged entities. However, despite the potentially high transferability of AI expertise across corporate functions and organizations (Gathmann and Schönberg, 2010), our analysis reveals limited evidence of post-merger AI skill mobility or spillover effects. This suggests that the observed performance improvements are driven more by the strategic complementarity of AI and data capabilities than by workforce integration.

Another explanation could be that high-AI firms achieve superior merger outcomes due to their pre-merger financial strength or better governance (Wang and Xie, 2009). However, we find that high-AI acquirers outperform even when their pre-merger financial performance, measured by return on assets (ROA) and return on equity (ROE), is weaker. This highlights that the synergies observed are not merely the result of superior management or operational efficiency but are primarily attributable to the unique contributions of AI talent.

Our research contributes to the literature in three key ways. First, it advances the understanding of the determinants of M&A decisions and outcomes. The existing literature has documented several motives for acquisitions, such as acquiring innovations (Ahuja and Katila 2001; Celik, Tian, and Wang, 2022; Kaufmann and Schiereck, 2023), organizational capital (Li, Li, Wang, and Zhang, 2018), and human capital (Ouimet and Zarutskie, 2020; Chen, Gao, and Ma, 2021; Chen, Hshieh, and Zhang, 2024). Notable works, such as those examining the role of product and innovation synergies (Hoberg and Phillips, 2010; Makri, Hitt, and Lane, 2010; Bena and Li, 2014), highlight the importance of strategic alignment in M&As. Add to this line of discussion, we show that the strategic alignment between AI capabilities and data assets within mergers and acquisitions can create value, thus identifying a novel source of acquisition synergy in the era of advanced AI development. This insight provides a fresh perspective on how technological advancements influence M&A strategies and outcomes.

Second, we contribute to the growing body of literature on the role of AI in corporate finance and the sources of value creation by AI for corporations (e.g., Rammer, Fernández, and Czarnitzki, 2022; Czarnitzki, Fernández, and Rammer, 2023; Acemoglu et al., 2024). Prior research has demonstrated that AI creates value in various ways, such as enhancing operational efficiency, increasing labor productivity, and fostering innovation (Graetz and Michaels, 2018; Agrawal, Gans, and Goldfarb, 2019; Acemoglu and Restrepo, 2019; Frank et al., 2019; Gofman and Jin, 2022; Babina et al., 2024). Using the context of M&As, we provide empirical evidence that a major channel of value creation by AI lies in its strategic integration with data assets, echoing the findings by Beraja, Yang, and Yuchtman (2023). While their study emphasizes how the use of data assets helps develop AI innovations, our paper suggests the proactive actions taken by firms with AI capabilities in seeking synergies and integrating with data assets in the market.

Finally, our study adds to the literature on the role of labor skills in corporate finance. The extant literature has established that labor upskilling benefits firms in multiple ways, including boosting productivity and driving innovation (Bresnahan, Brynjolfsson, and Hitt, 2002; Brynjolfsson and McAfee, 2014; Brynjolfsson, Mitchell, and Rock, 2018). While the literature discusses the replacement of labor by automation technologies like AI (Acemoglu and Autor, 2011; Acemoglu and Restrepo 2018), high-skill labor is the major inventor, bearer, and user of new technologies (Tambe, 2014; Autor, 2015; Acemoglu and Restrepo, 2019). Using detailed labor skills data reported in employee profiles, we show that a specific type of upskilling – AI expertise – contributes to significant value creation by firms. In particular, AI skills provide firms with a competitive edge in acquiring and effectively utilizing data assets, as well as in fostering innovation. This evidence aligns with the trend of increasing investments in AI talent by firms over the past decades, highlighting its pivotal role in corporate success.

2. Literature Review

2.1 Drivers of M&A decisions and post-merger outcomes

Mergers and acquisitions represent a significant strategic maneuver for firms seeking to enhance their competitive positioning by acquiring valuable resources from target companies. One primary motivation for M&A is the pursuit of specific resources. Numerous studies, such as those by Ahuja and Katila (2001), Celik, Tian, and Wang (2022), and Kaufmann and Schiereck (2023), highlight that technological acquisitions can significantly enhance the innovation performance of acquiring firms, particularly in technology-intensive industries. Their longitudinal studies indicate that firms acquiring technology-oriented assets tend to experience greater innovation outcomes compared to those that do not. Beyond technology, the acquisition of skilled labor is another critical driver of M&A activity. Research by Ouimet and Zarutskie (2020), Chen, Hshieh, and Zhang (2024), Lee, Mauer, and Xu (2018), and Abramova (2024) underscores the significance of human capital as a key resource sought in acquisitions. While the pursuit of technological resources and skilled labor has long been recognized as primary motivations for M&A, our paper introduces a new dimension to this understanding: the increasing importance of data as a critical resource in the digital era.

When acquirers pursue resources from the target, the complementarity between the two largely determines the outcome. This notion is further supported by Bena and Li (2014), who argue that synergies derived from combining innovation capabilities are crucial drivers of acquisitions. Capron and Pistre (2002) provide empirical evidence that acquirers are more likely to earn abnormal returns when they successfully integrate resources from the target firm, emphasizing the importance of resource transfer in realizing the benefits of M&A. When it comes to the source of such complementarity, theoretical modeling by Makri, Hitt, and Lane (2010) indicates that complementarity in both scientific and technological knowledge enhances post-merger innovation performance by fostering higher quality and more novel inventions. Works such as Hoberg and Phillips (2010) and Yu, Umashankar, and Rao (2016) provide empirical evidence that acquirers also value complementarity in product portfolios as a driver of M&A success.

Furthering the idea of complementarity, we argue that data assets and AI capabilities represent a new type of resource complementarity driving M&A activity in the digital economy. This perspective is supported by the growing body of literature recognizing data as a vital asset and emphasizing its combination with relevant skillsets. Data is increasingly recognized not merely as a byproduct of economic activities but as a vital asset that can drive innovation, enhance productivity, and facilitate informed decision-making across various sectors (Brynjolfsson, Hitt, and Kim, 2011; Jones and Tonetti 2020; Cong, Xie, and Zhang 2021; Farboodi and Veldkamp 2021; He, Huang, and Zhou, 2023). However, the value of data is maximized when utilized by workers possessing the necessary AI skills, as presented in the seminal work of Acemoglu and Autor (2011). This idea is further supported by the empirical work of Tambe (2014), who demonstrates the complementary relationship between data analytics and human capital in enhancing firm performance.

2.2 The impact of AI on firm performance

The integration of AI into corporate practices has emerged as a transformative force, reshaping various aspects of business operations. Levy and Murnane (2003) and Bessen (2015) describe AI, as a specialized form of computer capital, capable of substituting for routine cognitive and manual tasks while simultaneously complementing non-routine problem-solving and interactive activities. Brynjolfsson, Rock, and Syverson (2019) model AI as a general-purpose technology (GPT), emphasizing that its full potential is unlocked through complementary innovations, with productivity gains likely materializing in later stages of adoption. These conceptualizations are further supported by emerging empirical evidence. Studies by Van Roy et al. (2020), Behrens and Trunschke (2020), and Czarnitzki, Fernández, and Rammer (2023) demonstrate a positive correlation between AI adoption and firm performance.

The mechanisms driving this enhanced performance are diverse. One established area of research focuses on the role of AI in labor demand and labor productivity. Various studies find that AI can both replace and augment the human workforce, as evidenced by Graetz and Michaels (2018), Frank et al. (2019), Acemoglu and Restrepo (2019), Yang (2022), and Chen and Wang (2024). Both effects contribute to the value of firms by reducing labor costs or improving labor productivity. Furthermore, Agrawal, Gans, and

Goldfarb (2019) emphasize AI's role as a powerful predictive tool. This argument is empirically supported by Brynjolfsson et al. (2011) and Shamim et al. (2020), who find that firms embracing data-driven managerial decisions, facilitated by AI's predictive capabilities, outperform competitors. This improved decision-making reduces errors and enhances operational efficiency. Finally, AI serves as a catalyst for innovation. Babina et al. (2024) attribute enhanced firm performance to increased product innovation driven by AI, while Beraja, Yang, and Yuchtman (2023) demonstrate that innovative output is heavily reliant on a firm's data assets, which AI can effectively leverage.

3. Data and Sample

3.1. Data sources

As AI-skilled labor is a critical factor in the deployment of AI systems (Babina et al., 2024), we propose a skills-based measure of firms' AI capability based on AI human capital information. We obtain individual employees' profiles from LinkedIn, the largest professional social network, which covered 169.9 million users in the US as of 2019, representing the vast majority of the US workforce. The LinkedIn profile dataset offers a wealth of self-reported information about each individual employee. This granular data includes details about their educational background (including institutions attended, time range of attendance, and fields of study), professional experience (including employer name, job title, start and end dates), skills, and other personal information.

We collect firm-year-level financial information from Compustat, daily stock information from CRSP, and M&A deal information from the SDC M&A Platinum database through WRDS. The financial data from Compustat is used to construct firm-year-level control variables, and daily stock information from CRSP is mainly used to calculate cumulative abnormal returns (CARs). The SDC database contains M&A deal characteristics, including deal announcement date, deal value, payment type, shares owned by the acquirer, and deal status.

To capture target firms' data intensity, we use Item 1A of 10-K filings to obtain data risk information, as described in Section 4.2. In addition, to measure post-merger innovation performance, we collect firm-year patent data from Extended KPSS dataset following Kogan et al. (2017), and AI patent data from Artificial Intelligence Patent Dataset (AIPD). AIPD is developed by the USPTO's Office of the Chief Economist to help researchers and policymakers study AI invention (Pairolero et al. 2024). The dataset identifies AI patents and pre-grant publications from US patent documents published between 2011 and 2019 using machine learning models.[1]

3.2 Sample construction

We start with the SDC dataset to construct our acquisition sample between January 1, 2009, and December 31, 2019. We restrict targets to US companies and only include transactions that change the control of target firms. Following Masulis et al. (2007) and Gokkaya et al. (2023), we apply the following filtering rules: (1) Deals that occur between January 1, 2009, and December 31, 2019. (2) Targets are US companies. (3) The acquirer owns less than 50% of the target before the deal announcement and controls more than 50% of the target after the transaction. (4) The deal value disclosed

[1] The current AIPD database version only covers the years from 2011-2019.

in SDC is more than $1 million and is at least 1% of the acquirer's market value of equity measured on the 11th trading day prior to the announcement date.

Next, we prepare other firm-level covariates. The financial data of acquirers and targets come from the Compustat database, and stock return information of acquirers (all acquirers are publicly listed in our sample) comes from the CRSP database. We merge these data with the filtered SDC deals as of the year prior to each deal announcement date indicated in SDC. This procedure results in a total of 11,921 unique deals after excluding non-public acquirers.

We then match the firm list of acquirers and targets in this merged dataset to the LinkedIn dataset. Specifically, we match employers in the LinkedIn data to the firm list extracted from the SDC-Compustat-CRSP merged data, including acquirers and targets. Our matching process consists of two steps. First, we use company website URLs available from Compustat as primary identifiers to match with the LinkedIn data, as most companies on LinkedIn list their official website URLs. We conduct internet searches for the missing URLs. Second, we manually match the remaining companies by name and other available information, such as location, year founded, and industry. We achieve a matching rate of about 80%.

Within this matched sample, we use employee profile data to compute measures of AI skills and AI employees at the firm-year level. The employee profiles in LinkedIn are at the employee level, where we can see each worker's skills, start date, end date, and employer for each of their employment. This allows us to count the number of AI skills (defined below in Section 4.1) owned by each individual and identify their workplace for each month. Consequently, we can determine all the workers employed by each firm in each month and aggregate information such as the number of employees, AI employees (employees who own at least one AI skill), and AI skills (owned by all of its employees) to the firm-year level. [2]

Finally, we merge the firm-year-level AI measures with the acquirer and target of each deal in the SDC-Compustat-CRSP merged data according to the year preceding the deal announcement date. After excluding missing values for dependent and independent variables, the final sample consists of 3,904 unique transactions, with the AI information constructed from 24,959,167 employment records of 13,011,554 employees involved.

4. Variables and summary statistics

4.1 AI measures

We first employ the AI-related skill list provided by Babina et al. (2024) to define AI skills.[3] Then, we identify and count these AI skills in the LinkedIn employee profiles for each employee. If an employee reports at least one AI skill, this individual is identified as an AI employee. For example, an employee possessing skills such as "Deep Learning" and "Xgboost" would be classified as an AI employee with two AI-related skills. Next, we aggregate the employee-level AI data to the firm-year level. Since we know each employee's workplace in each month, we average the number of AI employees and

[2] We compute the year-level information using the average value of months in each year.

[3] The skill list includes 67 most AI-related skills, such as Deep Learning, Xgboost, NLP, and Machine Learning.

AI skills to the employer-year level (i.e., firm-year level), using values of all months over each year.

For each deal, the acquirer's AI skills and AI employees are defined as the acquirer's firm-year number of AI skills (*Acq_AI Skill*) and AI employees (*Acq_AI Employee*), respectively, as of the year prior to the deal announcement date. The same definitions apply to the target AI measures at the deal level. The natural logarithm of acquirers' AI measures serves as the main independent variable for subsequent analyses, defined as *LnacqAIskill* = *log(1* + *Acq_AI Skill*) and *LnacqAIemp* = *log(1* + *Acq_AI Employee*).

After constructing the AI measures, we plot the trend of AI skills and AI employees over time in our M&A sample. Figure 1 shows a consistent upward trend in both AI measures over time, consistent with previous literature (Babina et al., 2024). In particular, Panel A of Figure 1 shows an obvious increase in both acquirers' and targets' AI skills. Panel B shows similar patterns in both acquirers' and targets' AI employees. These upward trends confirm that firms are placing growing emphasis on AI capabilities. Moreover, regardless of the AI measure used, the acquirers exhibit a faster growth rate than the targets, highlighting the acquirers' greater initiative and significance in leveraging AI.

Additionally, we create a map of the geographic distribution of AI skills (Figure 2). We geolocate AI skills using the work locations of their holders, and aggregate this data at the county level. As shown, the distribution of AI skills in our sample closely aligns with the locations of major US universities and technology hubs. Notably, some metropolitan areas, such as the San Francisco Bay Area, Seattle, Boston, New York City, Austin, Denver, and the Washington D.C. area, appear as prominent red and orange zones, suggesting a strong correlation between AI talent and established tech hubs, confirming the validity of our AI measures constructed from LinkedIn employee skills.

4.2 Data intensity measures

We introduce a novel approach based on the frequency of data security keywords in Item 1A of 10-K filings to construct the data intensity measure. We posit that firms with larger and more complex datasets inherently face heightened data security risks due to the challenges of safeguarding sensitive information, complying with evolving privacy regulations (e.g., GDPR, CCPA), and mitigating breach-related costs. Therefore, the volume of data a company possesses is inherently linked to its data security risk: the greater the amount of data a company generates, the more likely data security risks occur and the higher the potential costs. To quantify such the relationship, we count word frequency in Item 1A of 10K in which such risks are systematically disclosed, as the SEC mandates transparent reporting of material risks, including cybersecurity threats. Specifically, we obtain a word list from the Data Security Glossary maintained by Cloud Security Alliance (CSA), a leading organization committed to awareness, practical implementation, and certification for the future of cloud and cybersecurity. We then employ Python to calculate the word frequency of the technical terms in the list, the prevalence of data security keywords in Item 1A. We define data intensity (*DataIntense*) as:

$$DataIntense = (\#\ \text{data risk keywords} / \#\text{total words})$$

This normalized measure accounts for document length variability and captures the relative emphasis on data security risks, which we argue correlates with the scale and complexity of a firm's data assets.

To test the data-driven hypothesis, we also analyze the changes in the number of data analysts (i.e. data analytics specialists) and AI-skilled data analysts employed by the acquirer before and after the announcement date. To measure these changes, we construct relevant indicators based on the job titles from LinkedIn data for each work experience. We identify data analysts from the LinkedIn data by identifying the "data" keyword in the employee's job title (e.g., an employee with a job title of "senior data analyst" falls into this category).

4.3 Other variables

Our dependent variables include cumulative abnormal returns (CARs), indicator variable for acquirer-target pairing and post-merger performance measures such as Patent Application and Patent Citation. Following the approach commonly used in M&A literature (Gokkaya et al., 2023), we employ the event study methodology to calculate the CAR of acquirers for each M&A event around the announcement date. Specifically, we estimate the market model in an estimation window of 180 to 11 days prior to the announcement date of each merger. The event window is defined as the period from 5 days before to 5 days after the announcement date. For each day within the event window, the abnormal return (AR) is calculated as the difference between the actual return and the predicted return by the market model. The CARs are calculated as the sum of ARs within the event window [-5, +5]. We use alternative event windows [-3, +3] and [-10, +10] for robustness.

The dependent variable for acquirer-target pairing sample, *Acquirer-Target*, is equal to one for the acquirer-target firm pair, and zero for the control firm pairs that form the control group. *Patent Application* is defined as the logarithm value of sum of patents applied for by the acquirer and the target for the period before the acquisition and the number of patents applied for by the combined firm for the period after the acquisition. *Patent Citation* is defined as the logarithm value of sum of citation counts received by patents applied for by the acquirer and the target for the period before the acquisition and the citation counts received by patents applied for by the combined firm after the acquisition.

We compute control variables used in the subsequent analyses, including acquirer characteristics such as the natural logarithm of firm market equity (*Size*), *Tobin's Q, Leverage*, *ROA*, the natural logarithm of intangible assets (*Lnintan*), and free cash flow (*Freecashflow*). We also control target characteristics including the natural logarithm of target AI skills (*LntarAIskill*) and *Tar_Hightech* and control deal characteristics including payment type (*Allstockdeal*), relative deal value (*Rel_Dealval*), *Tenderoffer*, *diversifying, Conglomerate* and *samestate*. Detailed definitions of all variables are provided in Table A1 in the Appendix. Table 1 presents the summary statistics of the constructed variables of the final sample.

4.4 Summary statistics

Summary statistics are reported for acquirer characteristics in Panel A, target characteristics in Panel B, deal characteristics in Panel C, combined firm characteristics in Panel D and employee/experience characteristics in the LinkedIn sample in Panel E. The matched LinkedIn dataset consists of 24,959,167 M&A-relevant work experience records (i.e., in firms involved in M&A transactions) of 13,011,554 employees, 36.15% of whom are female and 49.15% of whom are male[4]. The average number of work experiences in a firm involved in M&A transactions for the sample employees is 1.918. The average duration of these work experiences is 55.926 months. Additionally, each employee, on average, possesses 0.023 AI-related skills, with 98.8% of them not having these skills, highlighting the scarcity of AI talent.

We find that an average acquirer in our final sample has an average of 22.82 AI talents per month in the year prior to the deal (1.64% of all employees), with an average of 31.67 AI skills. In contrast, an average target firm in our sample has an average of 4.91 AI talents per month in the year prior to the deal (1.39% of all employees), with an average of 6.44 AI skills. This distribution is consistent with our expectations that acquirers have more AI human capital and skills than targets, which can potentially create synergy when merged with targets possessing large data assets.

5. Empirical Results

5.1 The impact of acquirer AI capabilities on acquisition announcement returns

5.1.1 Baseline result

We begin by examining the impact of acquirer AI capabilities on acquisition announcement returns. In our context, a greater CAR indicates that the market has reacted

[4] The remaining 14.7% are not reported.

favorably to the announcement of a merger or acquisition. We use CARs as the dependent variable and estimate the model below:

$$CARs_{i,t} = \alpha + \beta_1 Acquirer's\ AI_{i,t-1} + \beta_2 AcquirerControls_{i,t-1} + \beta_3 TargetControls_{i,t-1}$$
$$+\beta_4 DealControls_{i,t} + Acquirer\ Industry\ FE + Year\ FE + \varepsilon_{i,t}, \quad (1)$$

where $Acquirer's\ AI_{i,t-1}$, the primary variable of interest, representing two measures of acquirer's AI capability of deal i in year *t-1*. One is $LnacqAIskill_{i,t-1}$, which denotes the average AI skills in acquirers in the year prior to the announcement date. The other is $LnacqAIemp_{i,t-1}$, which denotes the average AI employees in the acquirer in the year prior to the announcement date. Following the M&A literature, we control for a list of acquirer characteristics ($AcquirerControls_{i,t-1}$), including the natural logarithm of firm market equity (*Size*), *Tobin's Q, Leverage*, *ROA*, the natural logarithm of intangible assets (*Lnintan*), and free cash flow (*Freecashflow*). We also control several target characteristics ($TargetControls_{i,t-1}$) and deal characteristics ($DealControls_{i,t}$), including the natural logarithm of target AI skills (*LntarAIskill*), *Tar_Hightech*, payment type (*Allstockdeal*), relative deal value (*Rel_Dealval*), *Tenderoffer*, and *Conglomerate*. Acquirer industry fixed effects (based on six-digit SIC code) and year fixed effects are incorporated to account for inherent industry characteristics and annual macroeconomic conditions.

The results are presented in Table 2. Columns (1) to (3) show the results when using the count of AI skills of all employees (*LnacqAIskill*) as the main independent variable. We alternate time window lengths ([-3,+3], [-5,+5], [-10,+10]), and observe that *LnacqAIskill* consistently exhibits a positive and significant coefficient, suggesting a positive association between acquirers' AI capabilities and their acquisition performance. In columns (4) to (6), we use the count of acquirer's AI employees as the main independent variable and the results remain quantitatively similar. Our findings provide evidence that AI talent is a valuable asset that can contribute to firm value in the context of M&A. For simplicity, we adopt CAR[-5,+5] in all the ensuing analyses, as alternative windows yield highly consistent results.

5.1.2 Instrumental variable approach

To address endogeneity concerns, we employ an instrumental variable (IV) strategy that exploits firm's exposure to AI talents supply following Babina et al. (2024). This method isolates exogenous variation in firms' AI skill acquisition stemming from local talent supply, reducing bias from unobserved demand factors affecting both AI investments and firm performance.

To be specific, we employ a distance-based instrument: the share of AI graduates that graduate from universities within 100 miles of a company's headquarters, weighted by the size of each university. The IV is constructed in three stages:

First, identifying AI-strong universities. We classify universities as AI-strong university if the average number of AI researchers during 2006–2008 (ex ante M&A sample period) is in the top 3% of the distribution across all universities. University-year level data for AI researchers is provided by Babina et al. (2024). This classification ensures that universities' AI-talent-producing abilities reflects pre-determined characteristics unaffected by later firm decisions. Second, measuring geographic proximity of firms and AI-strong universities. Using U.S. Census county distance data from NBER, we calculate the distance between the counties of each firm's headquarter and AI-strong universities.

We retain universities within a 100-mile radius, as closer proximity strengthens labor market spillovers. Third, construct the size-weighted IV. For each firm-year, we aggregate the share of AI graduates from AI-strong universities within 100-mile county distance, weighted by university size to construct the firm-year IV for firms' AI skills. The IV is defined as:

$$IV_{it} = \sum_{j \in J_{it}} \frac{AI\_Grads_{jt}}{All\_Grads_{jt}} \times Weight\_size_{jt} \quad (2)$$

where AI_Grads_{jt} is the number of fresh graduates from university *j* in year *t* whose first job after graduation is an AI-skilled job; All_Grads_{jt} is the total number of fresh graduates from university *j* in year *t*; J_{it} represents the set of AI-strong universities within a 100-mile radius of firm *i*'s headquarter in year *t*; and $Weight\_size_{jt}$ is the size-based weight of university *j* in year *t* (defined in Equation 3). Data for fresh graduates from each university is from Babina et al. (2024).

The size-based weight of university in Equation 2 is defined as:

$$Weight\_size_{jt} = \frac{ln(All\_Grads_{jt})}{\sum_{j \in 100-mile\ radius} ln(All\_Grads_{jt})} \quad (3)$$

where All_Grads_{jt} is the total number of fresh graduates from university *j* in year *t*. This size-based weight represents the proportion of graduates from university *j* among all AI-strong universities within a 100-mile radius.

We then link the firm-year IV to our deal-level baseline sample using the IV for each acquirer firm at the year *t+1* relative to the deal announcement because IV in these years performs a great first stage outcome, which allows it to serve as a suitable instrument.

Table 3 shows instrumental variable estimate results. Column (1) and (3) report the first stage of the instrument, where we regress our key independent variable (*LnacqAIskill*) on the instrument, which measures acquirer firm-level exposure to the supply of AI talents. Column (2) and (4) report the second stage results. All specifications control for acquirer-industry sector fixed effects and year fixed effects. Columns (1)-(2) show the results without baseline control variables. Columns (3)-(4) include the baseline controls: acquirer characteristics (*Size, Tobin's Q, Leverage, ROA, Lnintan and Freecashflow*), target characteristics (*LntarAIskill and Tar_Hightech*) and deal characteristics (*Allstockdeal, Rel_Dealval, Tenderoffer and Conglomerate*).

The instrument has a strong first stage with positive and significant relationship between IV and core independent variable (*LnacqAIskill*), and with F-statistics above 10. Next, the 2SLS estimates results show a positive and significant effect of acquirers' AI capability on CAR[-5,+5]. When baseline controls are included, a one-standard-deviation increase in AI capability leads to a 5.76% increase in CAR[-5,+5]. The IV estimation results are consistent with those of OLS, both demonstrating the positive impact of acquirer AI capability on acquisition performance.

5.2 Source of Value Creation by AI

5.2.1 The effect of combining AI with data assets

After documenting that firms with more AI skills tend to have greater announcement returns, the next question is what is the source of this value creation. AI products, at their core, resulted from learning patterns and generating insights by analyzing vast quantities of data using the appropriate techniques. We thus posit that a primary function of AI employees within acquiring firms is to unlock the potential that emerges from combining AI skills with the target's stocks of data assets. When an acquirer's AI expertise joins hands with a target's rich data assets, this creates value by enabling the development of more sophisticated and effective AI solutions. Therefore, we argue that successful AI-driven M&A arises when: (1) the acquirer possesses advanced AI technology but lacks sufficient data to train and optimize its algorithms, and (2) the target possesses data-rich assets but lacks the AI capabilities to leverage them effectively.

To verify the conjecture, we construct a novel measure of firms' data intensity based on the frequency of data security keywords in Item 1A of its 10-K filings, as described earlier. We match the computed data intensity measure to target firms as of the year prior the deal announcement. Then, to test whether the data intensity in the target firm helps building up synergy with AI talents of the acquirer and causes the positive CAR, we partition target companies in our sample by the median values of target data intensity, into high-data subgroup (*Hightardata*, equals 1 when *DataIntense* of the firm is greater than the median) and low-data subgroup (*Lowtardata*, equals 1 when *DataIntense* of the firm is lower than the median). We then re-estimate Equation (1) for these two groups. The result is reported in column (1)-(2) in Table 4. The positive and significant association between acquirer AI and CAR are only observed in the acquisition subgroup with high data intensity targets. Economically, a one-standard-deviation increase in *LnacqAIskill* leads to a 1.76% increase in CAR for acquisitions of data-intensive targets. The results imply that it is the target's data assets that creates synergistic value with acquirer AI expertise.

It is possible that targets with high data intensity are those with high AI capabilities as well, and it is the overlap of AI expertise between acquirers and targets that constitutes the synergistic value of the merger. To rule out this idea, we partition our sample by the median-level of target's AI capabilities (computed the same way as acquirer's) into high target AI subgroup (*HightarAI*, equals 1 when the target has more AI skills than the median) and low target AI subgroup (*LowtarAI*, equals 1 when the target has less AI skills than the median). We tabulate the subsample test of high/low target firm AI capabilities in column (3)-(4) in Table 4. We can observe that acquirer AI (*LnacqAIskill*) is only positive and significant for the low-AI target subgroup. This result is inconsistent with acquirer-target AI overlap creating synergy for the merger, rather, it aligns with the notion that target is in needs of greater AI capabilities.

In addition to the subsample analysis, we next conduct more detailed analysis that directly shows the value creation by different combinations of acquirer and target characteristics in M&As. To this end, we add interaction terms between indicators of acquirer AI and target data characteristics. Specifically, *HighacqAI* (*LowacqAI*) is a dummy variable indicating whether the acquirer's AI capability is greater (lower) than the sample median. We construct target's AI capability indicators in a similar manner. Moreover, *Hightardata* (*Lowtardata*) indicates whether the target's data intensity is greater (lower) than the sample median. We incorporate interactions among these indicators into Equation (1) and re-conduct the estimation.

The results are presented in Table 5. Columns (1) to (3) show results when the dependent variable is CAR[-5,+5]. Only *Hightardata*HighacqAI* carries a positive and significant sign. These results suggest that the positive M&A return that we discover in the baseline regression is mainly driven by high-AI acquirers merging with data-intensive targets, confirming the existence of synergy between the two productive factors. On the contrary, coefficients on *HighacqAI*Lowtardata* and *LowacqAI*Hightardata* are both negative and significant, suggesting poor performance when high AI capability is combined with scarce data or when poor AI capability is integrated with rich data.

5.2.2 The pursuit of data by high-AI acquirers

If AI-data integration is an important source of value creation in M&As, it is sensible for high-AI firms to actively seek data assets in their business process to enhance their strategic position. To test this idea, before proceeding to the acquisition decisions made by high-AI firms, we first examine the decisions of these firms in hiring employees to conduct data related work (i.e., data analyst). We define data analyst by identify "data" keyword in the employee's job title (e.g., an employee with a job title of "senior data analyst" falls into the category).

Panel A in Figure 3 plots the time series of data analytics employees by high-AI acquirers and low-AI acquirers, respectively. We find that prior to the acquisition, acquirers with advanced AI capabilities exhibit a steadily increasing trend in hiring data analysts relative to industry-level prior to the deal, while acquirers without advanced AI capabilities exhibit a decreasing trend. This evidence implies that data analysts are valued by acquirers with strong AI capabilities before carrying out M&As. In addition, the divergence of the trends become even more pronounced when we plot employees with both data-related skills and AI skills (Panel B in Figure 3), suggesting that high-AI acquirers emphasize the vesting of both AI and data-related skills on their employees. Notably, the increasing trends of employees with data-related skills continue in the post-merger phase in both figures. Evidence from these figures point to the demand of high-AI acquirers for seeking AI-data integration, rather than a single skill alone.

Next, we conduct merger pairing analysis to investigate whether firms with strong AI capabilities actively seek data-intensive target in making acquisitions decisions. If acquiring a data-intensive target strengthens high-AI acquirers' strategic position and wins recognition from the market, such deals will be more likely to occur. To test this idea, we investigate what types of acquirers and targets are likely to form M&A pairs to exploit the opportunity of synergistic value creation. Our methodology follows Bena and Li (2014) by testing the likelihood of acquirer-target firm pairing using a conditional logit model. The sample consists of cross-sectional data as of the fiscal year end before the deal announcement, with one observation for each deal (real acquirer-target pair) and multiple observations for control deals (potential acquirer-target pairs).

To construct the pool of control deals, we form *Industry-* and *Size-Matched Control Sample* using propensity-score matches (PSM), which find up to five closest matches to the acquirer for each target, and up to five closest matches to the target for each acquirer. We also use *Industry-*, *Size-*, and *ROA-Matched Control Sample,* and *Industry-*, *Size-*, *ROA-*, and *Tobin's Q-Matched Control Sample* to ensure the robustness of our inference.[5] We then employ conditional logit model on the constructed sample after matching to estimate the following equation:

[5] The benefit of the method is that it controls for the potential influence of horizontal and vertical relatedness between industry pairs on merger formation likelihood, as highlighted by Fan and Goyal (2006) and Ahern and Harford (2014).

$$
\begin{aligned}
Acquirer - Target_{ijm,t} = \alpha + {} & \beta_1 HighacqAI_{im,t-1} * Hightardata_{jm,t-1} \\
& + \beta_2 HighacqAI_{im,t-1} * Lowtardata_{jm,t-1} \\
& + \beta_3 LowacqAI_{im,t-1} * Hightardata_{jm,t-1} \\
& + \beta_4 Acquirer\ Characteristics_{im,t-1} \\
& + \beta_5 Target\ Characteristics_{jm,t-1} \\
& + \beta_6 Deal\ Characteristics_{ijm} \\
& + Deal\ Group\ FE + \varepsilon_{ijm,t} \qquad (4)
\end{aligned}
$$

where the dependent variable, $Acquirer - Target_{ijm,t}$, is equal to one if the firm pair m with acquirer i and target j is the real acquirer-target firm pair, and zero otherwise. We construct high/low acquirer AI indicator variables ($HighacqAI_{im,t-1}$ / $LowacqAI_{im,t-1}$) and high/low target data indicator variables ($Hightardata_{im,t-1}$ / $Lowtardata_{im,t-1}$), relative to their respective sample medians, and incorporate their interactions in the regression model to test the probability of merger pairing for each combination in the sample. We include the following control variables: sales growth, the natural logarithm of intangible assets, size, Tobin's Q, leverage, ROA, and free cash flow of both the acquirer and the target, and two binary variables indicating whether the firms are in the same state and whether they are in different industry sectors.

The results from this analysis are presented in Table 6. Among all interaction terms, only *HighacqAI*Hightardata* bears a positive and significant coefficient, suggesting that M&A is more likely to occur between high-AI acquirers and data-intensive targets. This finding supports the notion that acquirers with strong AI capabilities seek out targets with rich data assets, as the combination of these resources can potentially generate significant value. This result is consistent with earlier findings that acquisitions with high-AI acquirers and data-intensive targets tend to have greater announcement returns, and that high-AI acquirers value data talents prior to the M&A process. Together, these findings regarding acquirers' pursuit of data-related labor and assets further validate our argument that the strategic complementarity between AI skills and data resources is an important factor driving M&A decisions and outcomes.

5.3 Realizing value of AI-data integration: Post-merger innovation output

The value creation resulting from the merger of high-AI acquirers and data-intensive targets has been well-documented and discussed. However, an important question that remains unanswered is what specific benefits are generated from AI-data integration. While the strategic alignment of AI and data can enhance various performance metrics post-merger, we argue that innovation stands out as a particularly crucial benefit. First, AI enables firms to learn more effectively and efficiently from vast quantities of data, significantly improving business decision-making, uncovering new patterns, and generating potentially innovative ideas (Babena et al., 2024). The literature also highlights the potential of data assets to drive innovation (Beraja, Yang, and Yuchtman, 2023). By successfully combining AI and data, firms can leverage AI's advanced data analysis capabilities and the rich information contained within data assets, thereby creating significant synergy potential through technological complementarity (Bena and Li, 2014).

The primary identification challenge in this analysis lies in the potential endogeneity of firm pair selection. The observed relationship between the pairing of acquirers with AI capabilities and targets with data, and the resulting post-merger innovation output, could be driven by the firms' endogenous decision to engage in a merger, rather than the actual impact of the “acquirer AI - target data” synergy on innovation. As previously discussed, acquisitions are more likely to occur between firms that already exhibit these complementary characteristics.

To address this concern and avoid biased estimates, we adopt a quasi-experimental approach inspired by Bena and Li (2014) and Seru (2014). Specifically, we use a control sample of withdrawn bids: deals that failed for reasons unrelated to the innovative activities of either merging firm. This approach allows us to treat the assignment of firm pairs to the treatment sample (completed deals) versus the control sample (withdrawn bids) as essentially random with respect to the innovation output variable we are analyzing. By comparing the innovation outcomes of completed deals with those of withdrawn bids, we can more accurately isolate the true impact of the “acquirer AI - target data” synergy on post-merger innovation.

We use samples of both treatment and control deals involving acquirer and target firms that were innovative prior to the bid to obtain a clear post-merger innovation effect following Bena and Li (2014), defined as having at least one patent application or citation. To construct the control sample, we start with 48 innovative withdrawn bids announced between 2009 and 2019, which have the necessary firm-level data in Compustat and CRSP. Next, we search relevant information from news articles and various other sources for each withdrawn bid to confirm that the failure of these bids was not related to the innovative activities of either merger partner.

Then, we select completed deals to form the treatment sample based on their comparability to control deals. Specifically, we focus on completed deals from 2009 to

2019 that meet the following criteria: (1) they involve innovative acquirers and target firms; (2) they occur in acquirer-target industry pairs that match those of the withdrawn bids in the control sample; (3) their announcement year falls within a three-year window centered around the announcement year of the control bids to minimize time-related differences. Table A2 in the Appendix details the number of remaining samples at each stage.

During the process of removing ineligible treatment samples, the number of control samples also decreases. This occurs because some control deals lack any eligible treatment deals for matching and are excluded from the sample. For instance, if the industry pair of a control deal does not match any completed deal, or if the matched completed deal falls outside the three-year window, the control deal will be dropped.

For each remaining control deal, we select the closest completed deal in terms of relative size ratio (i.e., the target firm's total assets divided by the acquirer's total assets) from the sample that meet the criteria mentioned above to become its treatment deal. This approach ensures that the treatment and control samples are comparable along key dimensions relevant to M&As, such as industry composition and time clustering (Roberts and Whited, 2013). We obtain patent and citation information from the Extended KPSS dataset following Kogan et al. (2017), and use the filing year of a patent as the time of its invention to measure a firm's innovation output (Hall et al., 2005).

We then estimate a difference-in-differences regression using a panel data set that contains information on deals in the treatment and control samples from five years before to five years after the deal announcement. We employ the following regression to test the impact of AI-data integration on innovation performance:

$$
\begin{aligned}
Patent_{ij,t} = {} & \alpha + \beta_1 After_{ij,t} + \beta_2 Treat_{ij} * After_{ij,t} \\
& + \beta_3 Treat_{ij} * After_{ij,t} * HighacqAI_i \\
& + \beta_4 Treat_{ij} * After_{ij,t} * Hightardata_j \\
& + \beta_5 Treat_{ij} * After_{ij,t} * HighacqAI_i * Hightardata_j \\
& + \gamma Combined\ Company\ Characteristics_{ij,t} \\
& + Deal\ FE + Year\ FE + \varepsilon_{ij,t} \qquad (5)
\end{aligned}
$$

where $Patent_{ij,t}$ represents combined patent applications (*Patent Application*) or combined patent citations (*Patent Citation*) of acquirer *i* and target *j* in each year *t*. *Patent Application* is defined as the natural logarithm of the sum of patent applications by the acquirer and the target for the period before the acquisition and the number of patent applications by the combined firm for the period after the acquisition. *Patent Citation* is defined as the natural logarithm of the sum of citation counts received by patents of the acquirer and the target for the period before the acquisition and the citation counts received by patents of the combined firm after the acquisition. $After_{ij,t}$ equals one for the post-merger time period (from *t+1* to *t+5*), and zero otherwise. $Treat_{ij}$ equals one for treatment deals, and zero otherwise. We construct indicator variables, $HighacqAI_i$ and $Hightardata_j$, which equal one if acquirer *i*'s AI capability and target *j*'s data intensity are higher than their respective sample medians. We then incorporate their interactions in the regression model. We control for financial variables of the merged firm, weighted by the relative size of the acquirer and the target. Deal and year fixed effects are included in all specifications.

The results are tabulated in Table 7, Panel A. The dependent variable is *Patent Application* in columns (1) and (2) and *Patent Citation* in columns (3) and (4). Across all specifications, the coefficients on *Treat*After*HighacqAI*Hightardata* bear positive and significant signs, suggesting that mergers with high-AI acquirers and data-intensive targets experience greater increases in innovation output after the merger relative to the control group not experiencing such mergers. To ensure robustness, Panel B presents the results from falsification tests where we assign pseudo announcement dates of treatment that are four years before its actual occurrence. The results indicate no significant difference in post-merger innovation output between the "treated" and control samples, which validates the findings in Panel A.

Next, we examine if the increase in innovative output is driven by AI patents. Beraja, Yang, and Yuchtman (2023) demonstrate that rich data content nurtures more AI innovations. By the same token, we conjecture that integrating AI technics with rich data assets is likely to produce more innovations that are particularly related to AI technologies. To identify AI patents, we employ the Artificial Intelligence Patent Dataset (AIPD), developed by the USPTO's Office of the Chief Economist to help researchers and policymakers study AI invention (Pairolero et al., 2024). The dataset identifies AI patents and pre-grant publications from US patent documents published between 2011 and 2019 using machine learning models.[6] AI patents are those whose patent documents published contain AI component technology based on the documents' text and citations (separately

[6] Since the AIPD consists solely of raw patent data, we merge it with patent and citation data from USPatents provided by Wharton Research Data Services (WRDS) to obtain common IDs needed to merge the datasets with our deal-level dataset.

identified for the eight AI component technologies from the AIPD, including machine learning, vision, natural language processing, speech, evolutionary computation, AI hardware, knowledge processing, and planning and control). For example, the Tensor Processing Unit (TPU) designed by Google to run neural network algorithms more efficiently is an AI patent that contains AI hardware.

We construct the treatment and control samples using the same filters as before, with the exception that restrictions on patents are now specific to AI patents. Using this updated sample, we re-estimate Equation (5), replacing the dependent variable with *AI Patent Application* and *AI Patent Citation* (industry-adjusted combined AI patent applications and citations). Results reported in Table 8 show that the coefficients on *Treat*After*HighacqAI* carry negative and significant signs across all columns, indicating that AI talent stock per se does not warrant greater innovative output after merger deals compared with the control group. Throughout all specifications with differing dependent variables, the coefficients on *Treat*After*HighacqAI*Hightardata* carry significantly positive signs consistently, suggesting that deals with high-AI acquirers and data-intensive targets generate more AI patents and receive more AI patent citations relative to the control deals not experiencing such mergers. This result emphasizes the AI-driven nature of post-merger innovation and validates our story: combined firms use AI techniques to analyze the data they acquire to innovate.

Furthermore, we again conduct a falsification test by assigning pseudo announcement dates that are four years prior to their actual occurrence and re-estimating the regression. The results, presented in Panel B, demonstrate that the post-merger innovation effect disappears between the fake "treated" and control samples, and hence validate that our findings in Panel A are driven by the de facto mergers of the two parties.

5.4 Alternative Explanations

5.4.1 Generalizability of AI skills

There are alternative explanations for our main findings. One such explanation pertains to the generalizability of AI skills. Employees with AI-related expertise are likely to adapt to different job positions or apply their skills across various job functions more easily. The acquiring firm could benefit from the broader applicability of its AI talent, either through the talents directly contributing to the target firm's operations or by leveraging their skills to improve resource management and operational efficiency, ultimately enhancing the performance of the combined firm. This explanation is in line with Lee, Mauer, and Xu (2018), who suggest that merged firms can benefit from the mobility of labor between the merging parties. In this case, the flow of generalizable labor skills can influence M&A decisions, particularly when the acquirer seeks to consolidate its workforce. Here, the data assets in the target firm represent just one type of asset upon which the acquirer's talent can apply their skills to generate profits and growth potential.

To test this possibility, we plot the labor mobility ratio (defined as the ratio of migrated employees to total headcount) between acquirer and target in Figure 4. We define migrated employees as those who have adjacent work records at the acquirer and the target firm within one M&A deal. Our observations reveal that AI employees do not exhibit a higher mobility rate, neither moving from the acquirer to the target nor vice versa. In fact, AI workers tend to have a higher retention rate than their non-AI counterparts, and labor flow is more likely to occur from the target to the acquirer. This may be due to the acquirer's comparative advantage in AI, which attracts more compatible talent with relevant skills. This finding contradicts the alternative explanation that labor mobility among AI employees would improve acquisition performance.

5.4.2 Acquirer fundamentals

It is also possible that strong AI capabilities are merely a reflection of acquirers' superior financial and management performance, as developing and implementing AI capabilities requires significant financial investment. In this scenario, the results documented in this study would represent strong firms acquiring weaker targets and leveraging their superior management to optimize a broader scope of assets or improve the target's operations, leading to better overall performance for the merged firm. If this were the case, the findings could not be specifically attributed to the contribution of AI skills.

To test this hypothesis, we partition acquirers into groups based on their pre-merger ROA (*High Acquirer ROA*/*Low Acquirer ROA*) and ROE (*High Acquirer ROE*/*Low Acquirer ROE*) relative to the sample median, and re-estimate the CAR regression separately for these subsamples. If the observed CAR were solely driven by pre-existing firm performance, we would not expect a positive impact of AI talent among acquirers with below-median financial performance. The results, presented in Table 9, show that the positive and significant effect of AI capability on acquisition announcement CAR is observed only for acquirers with below-median ROA or ROE. This finding suggests that the observed synergies are not merely a byproduct of well-managed firms performing well and applying their superior management to target firms. Instead, these results reinforce our conclusion that AI talent serves as a specific and distinct driver of value creation in M&A.

6. Conclusion

Leveraging a novel employee skills dataset, this paper examines the impact of corporate artificial intelligence on M&A outcomes. Our findings reveal that acquirers with strong AI capabilities are positively associated with acquisition performance, as measured by higher announcement returns. Further analyses support the idea that the integration between AI capabilities and data assets drives the observed superior performance. We also find that acquirers with strong AI capabilities actively pursue employees with data-related skills and target data-rich firms. Using exogenously withdrawn deals as a control group, we show that high-AI acquirers targeting data-rich firms experience significant increases in post-merger patent filings and citations, especially for AI-related patents. This suggests that integrating AI and data fosters innovation and long-term value creation.

This study advances our understanding of M&A decision-making by identifying a novel source of synergy in the AI era-the strategic alignment between AI capabilities and data assets-making one of the first contributions to the finance literature on this topic. Additionally, by highlighting the synergistic relationship between AI talent and data, our results also contribute to the ongoing academic (Acquisti, Taylor, and Wagman, 2016; Cockburn, Rock, and Syverson, 2018; Fainmesser, Galeotti, and Momot, 2023; Goldfarb and Que, 2023; Liu, Sockin, and Xiong, 2023) and policy (Ilan, Ronco, and Rosen, 2018;

McQuinn and Castro, 2019; Sundara and Narendran, 2023; Hutchinson, 2024) debate on the optimal balance between protecting data privacy and unleashing the full potential of economic efficiency.

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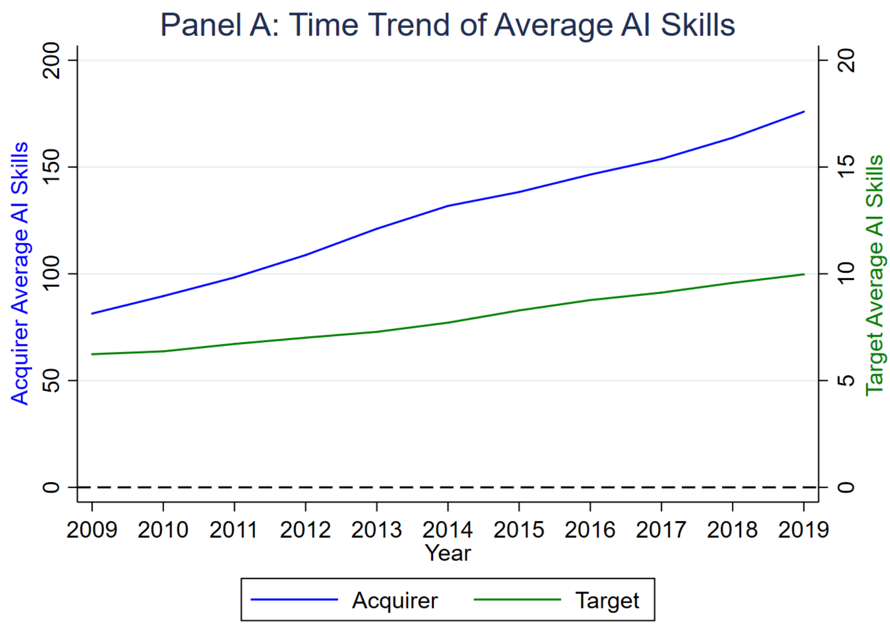
Figure 1. Time Series of AI capability

This figure shows the time series of the two measures of AI capability for acquirer firms and target firms. Panel A shows the average AI skills for firms during 2009-2019. Panel B shows the average AI employees for firms during 2009-2019. Both AI measures are constructed from LinkedIn data.



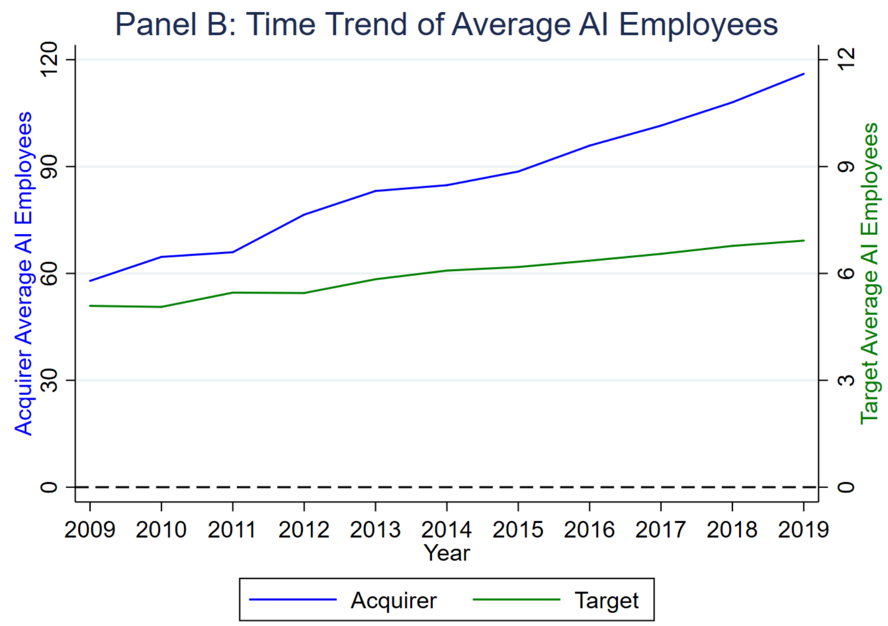


Figure 2. Geographic Distribution of AI Skills

We calculate the total number of AI skills of all employees in our sample at the county-level based on their reported work locations. The warmth of the color represents greater AI talent density.

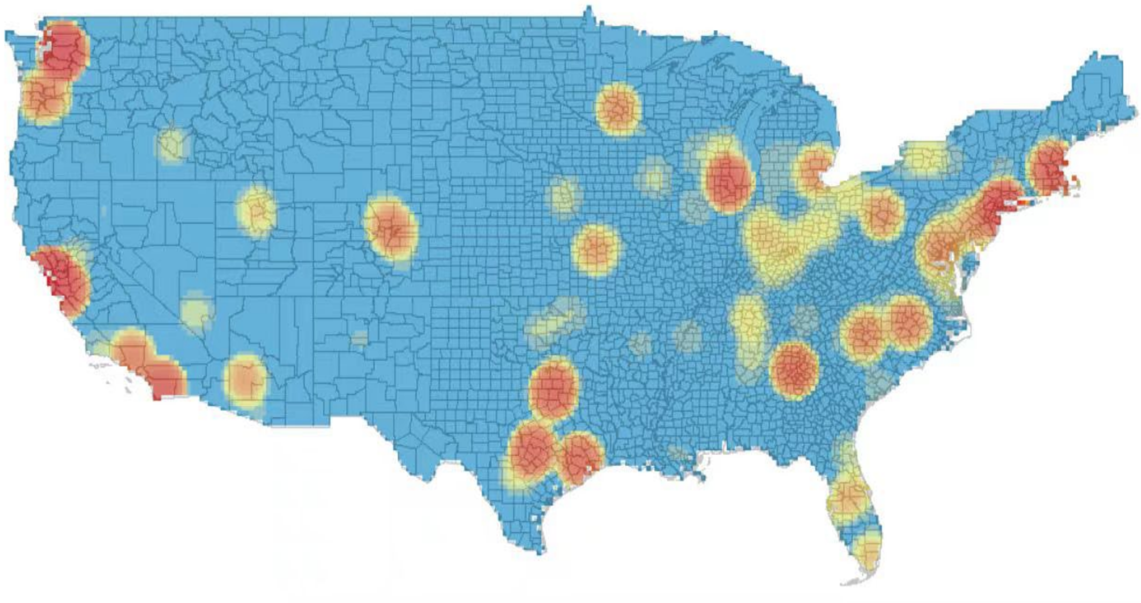


Figure 3. Time Series of Data Analytics Employees

This figure shows the industry-adjusted (based on 6-digit SIC industry codes) average number of data analysts in high-AI/low-AI acquirers during the period from 10 years before to 3 years after the announcement year of our sample deals. High/low-acquirer AI is determined according to the median of acquirer AI skills using LinkedIn data. We identify data analysts from the LinkedIn data by searching for the keyword "data" in job titles. The blue line represents data analysts in the high-AI group, and the green line represents data analysts in the low-AI group, both are industry-adjusted. Panel A plots the statistics for data analysts. Panel B plots the statistics for data analysts who also report AI-related skills in their skill set.

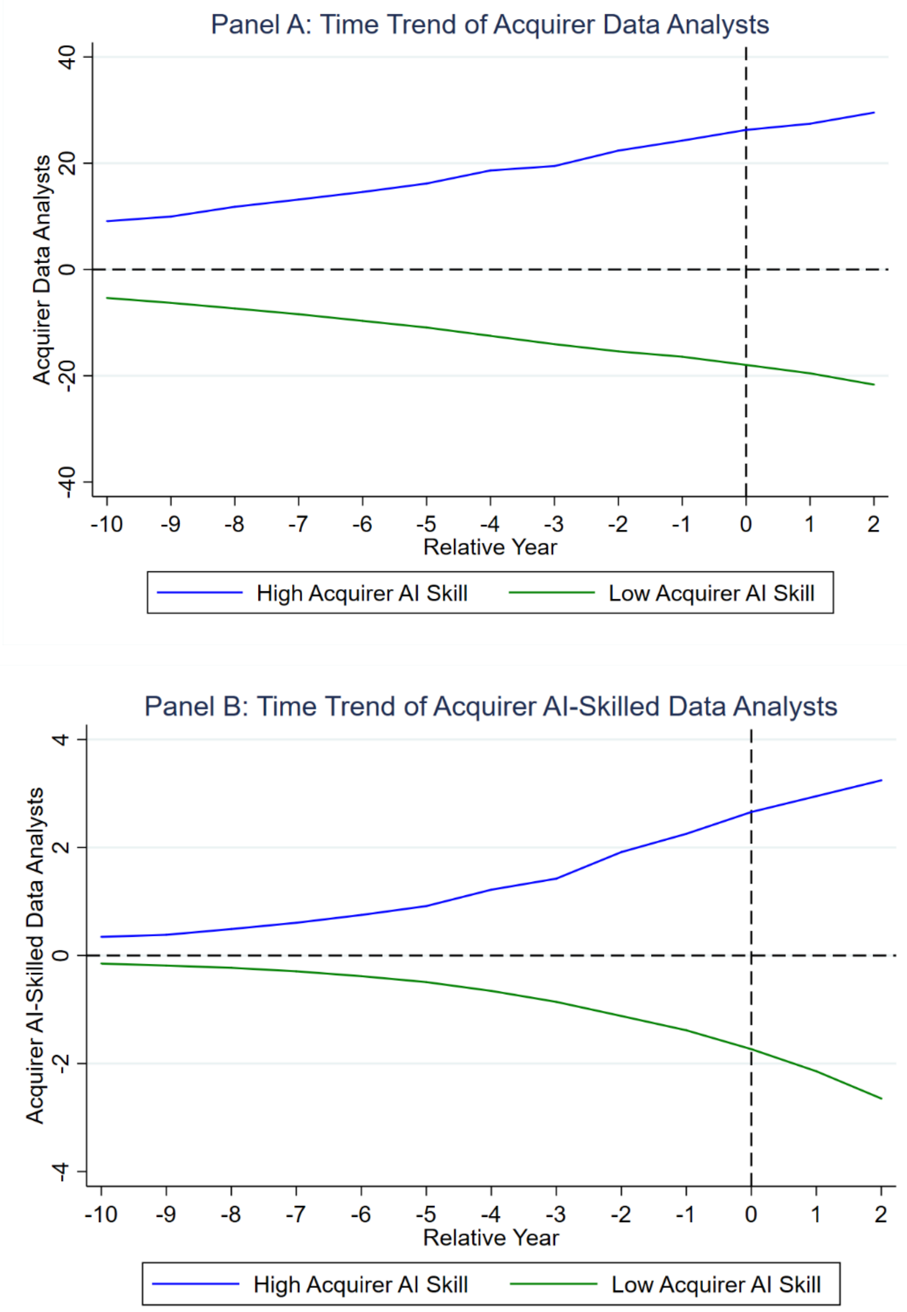


Figure 4. Labor Mobility Between Acquirer and Target for AI Talents and Other Employees
This figure presents the proportions of AI/non-AI talents' migrated employees relative to the total headcount, and the ratio of mobility direction. We define as those who have adjacent work records at the acquirer and the target firm within one M&A deal. The mobility direction (i.e., from acquirer to target or the opposite) is identified by tracing each employee's work experiences in the two firms. Labor mobility records are sourced from LinkedIn data. The statistics are computed for deals in our baseline sample.

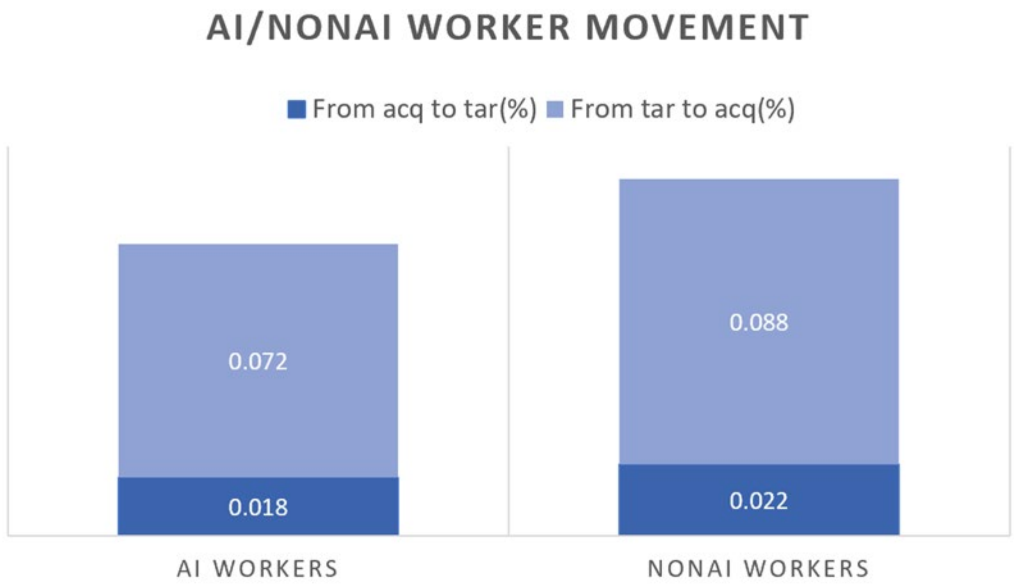


Table 1. Summary Statistics

This table reports descriptive statistics over the period from 2009 to 2019. Panels A, B, C and D present the mean, median, standard deviation, minimum, and maximum for the acquirer characteristics, target characteristics, deal characteristics and combined firm characteristics, respectively. Panel E presents employee/experience characteristics from SDC-LinkedIn matched data. M&A sample is drawn from the Thomson One Platinum Securities Data Company (SDC) M&A database and includes deals with worldwide public acquirers and US public and private targets announced between January 1, 2009, and December 31, 2019. A detailed description of variables can be found at Appendix.

	(1) N	(2) Mean	(3) SD	(4) Min	(5) Max
Panel A: Acquirer Characteristics:					
Acq_AI Employee	3,904	22.82	152.7	0	4,577
Acq_AI Skill	3,904	31.67	229.5	0	7,413
Acq_Employee	3,904	1,391.52	4,326	0	70,888
Freecashflow	3,904	0.037	0.156	-6.573	0.538
Leverage	3,904	0.283	0.230	0	6.207
LnacqAIskill	3,904	1.305	1.600	0	8.911
Lnintan	3,904	6.023	2.185	-2.453	12.31
ROA	3,904	0.022	0.165	-6.049	0.558
ROE	3,904	0.007	0.212	-7.689	1.366
Size	3,904	7.327	1.851	1.520	13.51
Tobin's Q	3,904	1.938	1.168	0.525	22.34
Panel B: Target Characteristics:					
DataIntense	628	0.525	1.520	0	20
LntarAIskill	3,904	0.571	1.071	0	8.022
Tar_AI Employee	3,904	4.911	53.22	0	2,867
Tar_AI skill	3,904	6.439	62.55	0	3,046
Tar_Employee	3,904	353.6	1,901	0	84,097
Tar_Hightech	3,904	0.299	0.458	0	1
Panel C: Deal Characteristics:					
Allstockdeal	3,904	0.030	0.171	0	1
CAR[-3,+3]	3,904	0.012	0.098	-0.624	1.843
CAR[-5,+5]	3,904	0.012	0.105	-0.607	1.835
CAR[-10,+10]	3,904	0.012	0.126	-0.625	1.525
Conglomerate	3,904	0.405	0.491	0	1
Rel_Dealval	3,904	-2.149	1.463	-7.770	5.881
Tenderoffer	3,904	0.039	0.195	0	1
Panel D: Combined Firm Characteristics:					
AI Patent Application	297	0.001	0.819	-2.577	3.718
AI Patent Citation	297	0.002	0.989	-3.241	3.693
Patent Application	368	3.125	1.939	0	7.944
Patent Citation	368	3.605	2.573	0	9.002
Panel E: Employee/Experience Characteristics:					
AI skills owned	13,011,554	0.023	0.229	0	16
Duration of Experience(month)	24,959,167	55.926	27.678	2	613
No. of Experience	13,011,554	1.918	1.483	1	32

Table 2. Acquirer AI Capabilities and Acquisition Announcement Returns

This table presents market-model cumulative abnormal returns (CARs) over the [-3, +3], [-5,+5] and [-10,+10] windows surrounding the M&A announcement dates, where the parameters of the market model are estimated using the CRSP value-weighted index over [-180, -11] days relative to the acquisition announcement date. Columns (1)-(3) presents the effect of acquirer's AI skills on CARs, and Columns (4)-(6) presents the effect of acquirer's AI employees (employees who own at least one AI-related skills). *LnacqAIskill* is defined as *log(Acq_AI skill +1)*, and *LnacqAIemp* is defined as *log(Acq_AI Employee+1)*. All specifications control for the 6-digit SIC acquirer-industry sector fixed effects and year fixed effects. Robust *t*-statistics adjusted for firm-level clustering are reported in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
	CAR[-3,+3]	CAR[-5,+5]	CAR[-10,+10]	CAR[-3,+3]	CAR[-5,+5]	CAR[-10,+10]
LnacqAIskill	0.004***	0.004***	0.004***			
	(2.88)	(2.59)	(2.75)			
LnacqAIemp				0.004**	0.004**	0.005***
				(2.56)	(2.56)	(2.77)
Size	-0.018***	-0.019***	-0.024***	-0.019***	-0.021***	-0.026***
	(-6.37)	(-6.55)	(-6.65)	(-6.18)	(-6.35)	(-6.73)
Tobin's Q	0.006***	0.008***	0.010***	0.005**	0.007***	0.009***
	(3.13)	(3.65)	(3.50)	(2.49)	(3.13)	(3.05)
Leverage	0.044**	0.039*	0.034*	0.046**	0.039*	0.032
	(2.22)	(1.96)	(1.80)	(2.11)	(1.81)	(1.64)
ROA	0.014	0.042	0.062	0.010	0.040	0.056
	(0.36)	(1.15)	(1.47)	(0.25)	(0.99)	(1.23)
Lnintan	0.007***	0.008***	0.009***	0.007***	0.008***	0.010***
	(3.25)	(3.58)	(3.51)	(3.26)	(3.48)	(3.49)
Freecashflow	0.053	0.025	0.034	0.050	0.016	0.026
	(1.13)	(0.54)	(0.73)	(1.01)	(0.32)	(0.53)
LntarAIskill	-0.001	-0.001	0.000	-0.000	-0.000	0.001
	(-0.30)	(-0.52)	(0.08)	(-0.09)	(-0.03)	(0.35)
Tar_Hightech	-0.004	-0.005	-0.008	-0.004	-0.004	-0.006
	(-0.97)	(-1.09)	(-1.36)	(-0.98)	(-0.72)	(-1.10)

Allstockdeal	-0.011	-0.009	-0.008	-0.014	-0.010	-0.003
	(-0.91)	(-0.78)	(-0.60)	(-1.23)	(-0.82)	(-0.18)
Conglomerate	-0.005	-0.008**	-0.005	-0.002	-0.005	-0.002
	(-1.49)	(-2.22)	(-1.15)	(-0.63)	(-1.40)	(-0.48)
Rel_Dealval	0.004***	0.005***	0.003	0.004**	0.004**	0.003
	(2.72)	(2.96)	(1.60)	(2.47)	(2.37)	(1.30)
Tenderoffer	-0.004	-0.005	-0.007	-0.004	-0.005	-0.005
	(-0.60)	(-0.63)	(-0.68)	(-0.53)	(-0.54)	(-0.53)
Constant	0.087***	0.090***	0.106***	0.092***	0.095***	0.115***
	(7.22)	(7.10)	(6.96)	(6.64)	(6.57)	(6.88)
Observations	3,865	3,865	3,865	3,830	3,830	3,830
R-squared	0.151	0.147	0.136	0.164	0.151	0.150
Acq. ind. FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes

Table 3. Acquirer AI Capabilities and Acquisition Announcement Returns: IV Estimates

This table reports the IV estimates for baseline results. Column (1) and (3) report the first stage of the instrument, where we regress our key independent variable (*LnacqAIskill*) on the instrument, which measures acquirer firm-level exposure to the supply of AI talents. The definition of the instrument is in Section 5.1.2. Column (2) and (4) report the second stage results. Columns (3)-(4) include the baseline controls: acquirer characteristics (*Size*, *Tobin's Q*, *Leverage*, *ROA*, *Lnintan* and *Freecashflow*), target characteristics (*LntarAIskill* and *Tar_Hightech*) and deal characteristics (*Allstockdeal*, *Rel_Dealval*, *Tenderoffer* and *Conglomerate*). Standard errors are clustered at firm level. Robust t-statistics are reported in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

	(1) LnacqAIskill	(2) CAR[-5,+5]	(3) LnacqAIskill	(4) CAR[-5,+5]
IV	3.124***		2.093***	
	(3.25)		(3.21)	
LnacqAIskill		0.024**		0.036**
		(2.12)		(2.11)
Size			0.590***	-0.033***
			(7.58)	(-2.94)
Tobin's Q			-0.106	0.010**
			(-1.58)	(2.58)
Leverage			-0.235	0.021
			(-0.63)	(0.98)
ROA			-0.027	0.036
			(-0.03)	(0.65)
Lnintan			-0.084	0.007*
			(-1.23)	(1.66)
Freecashflow			0.284	-0.017
			(0.25)	(-0.27)
LntarAIskill			-0.047	-0.002
			(-1.09)	(-0.53)
Tar_Hightech			0.249**	-0.010
			(2.10)	(-1.24)
Allstockdeal			0.243	-0.036*
			(0.91)	(-1.68)
Conglomerate			-0.025	-0.004
			(-0.28)	(-0.58)
Rel_Dealval			-0.044	0.003
			(-1.23)	(1.25)
Tenderoffer			-0.106	0.011
			(-0.51)	(0.88)
Observations	1,625	1,625	1,625	1,625
Acq. ind. FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
F Statistic	10.55	10.55	10.33	10.33

Table 4. Subsample Test: The Role of Target Data Intensity/ Target AI Skills

This table presents the results of CAR[-5,+5] regression on subsamples divided according to the median value of target data intensity and target AI skills. Acquisitions with targets whose data intensity is higher than the median fall into the high-target data intensity group (columns (1)), and the rest fall into the low-target data intensity group (columns (2)). Information on target data intensity is computed using a word frequency analysis on item 1a in 10-K filings. Acquisitions with targets whose AI skills of employees is higher than the median fall into the high-target AI group (columns (3)), and the rest fall into the low-target AI group (columns (4)). Target AI skills are computed using the same way as computing acquirer AI skills. Robust *t*-statistics adjusted for firm-level clustering are reported in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

	CAR[-5,+5]			
	(1) High target data	(2) Low target data	(3) High target AI	(4) Low target AI
LnacqAIskill	0.011*	-0.003	0.001	0.006***
	(1.89)	(-0.85)	(0.63)	(2.80)
LntarAIskill	-0.013	-0.010*		
	(-1.29)	(-1.74)		
Size	-0.009	-0.003	-0.019***	-0.021***
	(-0.54)	(-0.42)	(-3.49)	(-5.86)
Tobin's Q	0.014	0.026**	0.006*	0.009***
	(0.80)	(2.21)	(1.91)	(3.07)
Leverage	0.078	0.083*	0.059***	0.028
	(0.92)	(1.68)	(2.66)	(1.05)
ROA	0.297	-0.246	0.117**	0.018
	(0.78)	(-1.60)	(2.14)	(0.40)
Lnintan	0.006	0.010	0.007*	0.010***
	(0.43)	(1.46)	(1.85)	(3.61)
Freecashflow	0.168	0.009	-0.067	0.046
	(0.54)	(0.06)	(-0.94)	(0.80)
Tar_Hightech	-0.039	0.012	-0.004	-0.004
	(-1.04)	(0.58)	(-0.43)	(-0.58)
Allstockdeal	0.021	0.009	-0.032	0.006
	(0.46)	(0.33)	(-1.58)	(0.37)
Conglomerate	-0.023	0.020	-0.004	-0.009*
	(-0.91)	(1.29)	(-0.60)	(-1.96)
Rel_Dealval	0.004	-0.005	0.003	0.006***
	(0.26)	(-0.83)	(0.87)	(3.21)
Tenderoffer	0.015	0.002	0.005	-0.015
	(0.49)	(0.15)	(0.41)	(-0.94)
Constant	-0.042	-0.120**	0.081***	0.098***
	(-0.56)	(-2.29)	(3.50)	(5.91)
Observations	124	270	1,237	2,539
R-squared	0.457	0.318	0.215	0.171
Acq. ind. FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes

Table 5. Testing the Synergy between Acquirer AI and Target Data

This table estimates the impacts of different types of acquirer-target combinations on CAR[-5,+5]. We construct High/LowacqAI dummy and High/Lowtardata dummy according to the median value of acquirer AI skills and target data intensity, and incorporate their intersections to the right-hand side of the model. Columns (1), (2) and (3) examine the effect of high-AI acquirers combined with data-intensive targets, high-AI acquirers combined with data-poor targets, and low-AI acquirers combined with data-intensive targets, respectively. Robust *t*-statistics adjusted for firm-level clustering are reported in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

	CAR[-5,+5]		
	(1)	(2)	(3)
HighacqAI*Hightardata	0.048**		
	(2.27)		
HighacqAI*Lowtardata		-0.048**	
		(-2.27)	
LowacqAI*Hightardata			-0.048**
			(-2.27)
HighacqAI	-0.006	0.042**	-0.006
	(-0.50)	(2.36)	(-0.50)
Hightardata	-0.051***	-0.051***	-0.002
	(-2.97)	(-2.97)	(-0.16)
Size	-0.005	-0.005	-0.005
	(-0.91)	(-0.91)	(-0.91)
Tobin's Q	0.015*	0.015*	0.015*
	(1.73)	(1.73)	(1.73)
Leverage	0.057	0.057	0.057
	(1.49)	(1.49)	(1.49)
ROA	-0.146	-0.146	-0.146
	(-1.10)	(-1.10)	(-1.10)
Lnintan	0.010	0.010	0.010
	(1.64)	(1.64)	(1.64)
Freecashflow	0.115	0.115	0.115
	(0.84)	(0.84)	(0.84)
LntarAIskill	-0.009**	-0.009**	-0.009**
	(-2.10)	(-2.10)	(-2.10)
Tar_Hightech	0.014	0.014	0.014
	(0.87)	(0.87)	(0.87)
Allstockdeal	0.020	0.020	0.020
	(1.01)	(1.01)	(1.01)
Conglomerate	-0.001	-0.001	-0.001
	(-0.10)	(-0.10)	(-0.10)
Rel_Dealval	-0.006	-0.006	-0.006
	(-1.31)	(-1.31)	(-1.31)
Tenderoffer	-0.006	-0.006	-0.006
	(-0.55)	(-0.55)	(-0.55)
Constant	-0.073*	-0.073*	-0.073*
	(-1.84)	(-1.84)	(-1.84)
Observations	448	448	448
R-squared	0.289	0.289	0.289
Acq. ind. FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes

Table 6. Likelihood of Acquirer-Target Firm Pairing

This table reports coefficient estimates from conditional logit models using acquisitions of the US public targets and a control sample of potential deals matched using PSM. The dependent variable is equal to one for the acquirer-target firm pairing, and zero for the control firm pairs. Columns (1)-(3) present the results using three different control samples respectively. Definitions of all the variables are provided in the Appendix. All specifications include deal group fixed effects. Robust *t*-statistics adjusted for deal-level clustering are reported in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

	Acquirer-Target		
	(1)	(2)	(3)
	Ind-Size	Ind-Size-ROA	Ind-Size-ROA-Tobin's Q
HighacqAI*Hightardata	0.373*	0.480**	0.577***
	(1.93)	(2.29)	(2.61)
HighacqAI*Lowtardata	0.095	0.169	0.086
	(0.64)	(1.04)	(0.50)
LowacqAI*Hightardata	0.316	0.166	0.165
	(1.38)	(0.76)	(0.77)
Bothhighpatent	0.230	0.262	0.355
	(0.94)	(0.98)	(1.18)
Salesgrowth	0.654***	0.732***	0.422*
	(3.13)	(3.16)	(1.85)
Tar_Salesgrowth	0.172	0.248*	-0.134
	(1.16)	(1.70)	(-0.98)
Size	-0.076	-0.102	-0.139
	(-1.00)	(-1.26)	(-1.62)
Tar_Size	-0.106	0.095	-0.115
	(-0.96)	(1.10)	(-1.58)
Tobin's Q	-0.069	-0.107	-0.019
	(-0.96)	(-1.46)	(-0.29)
Tar_Tobin's Q	-0.061	-0.014	0.272***
	(-1.05)	(-0.27)	(4.68)
Leverage	0.340	0.862**	0.513
	(1.03)	(2.19)	(1.42)
Tar_Leverage	-0.230	0.341	0.416
	(-0.70)	(0.98)	(1.17)
Lnintan	0.070	0.082	0.129**
	(1.48)	(1.51)	(2.28)
Tar_Lnintan	-0.015	0.018	0.073
	(-0.31)	(0.38)	(1.51)
Freecashflow	1.944**	2.196**	2.408***
	(2.08)	(2.32)	(2.67)
Tar_Freecashflow	0.136	1.111	0.298
	(0.21)	(1.22)	(0.39)
ROA	0.197	-2.028**	-0.947
	(0.27)	(-2.10)	(-1.23)
Tar_ROA	0.476	-3.856***	-1.221*
	(0.96)	(-4.76)	(-1.93)
Diversifying	-4.270***	-4.553***	-4.380***
	(-19.67)	(-18.98)	(-20.19)
Samestate	1.016***	0.992***	0.841***

	(5.06)	(4.92)	(4.07)
Observations	4,623	4,603	4,447
Deal group FE	Yes	Yes	Yes

Table 7. Post-Merger Innovation Performance

This table presents results for the treatment effect of a merger on post-merger innovation output. Panel A presents regression results using a panel data set that, for each deal in the treatment sample (i.e., completed deals) and the control sample (i.e., bids withdrawn due to reasons exogenous to innovation), has observations running from five years prior to deal announcement to five years after deal announcement. The dependent variable is, in each year, the logarithm value of sum of the acquirer's and the target's innovation output measured by patent applications and citation. Panel B presents the results from falsification tests when we assign pseudo announcement dates to our sample mergers. Definitions of all the variables are provided in the Appendix. All specifications include deal and year fixed effects. Robust *t*-statistics adjusted for deal-level clustering are reported in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Panel A: Post-merger innovation

	Patent Application		Patent Citation	
	(1)	(2)	(3)	(4)
Treat*After*HighacqAI*Hightardata	0.422**	0.453*	1.189**	1.234**
	(2.13)	(1.78)	(2.42)	(2.20)
Treat*After*HighacqAI	-0.007	-0.157	-1.163***	-1.281**
	(-0.03)	(-0.64)	(-3.03)	(-2.68)
Treat*After*Hightardata	-0.640***	-0.600***	-0.660**	-0.522*
	(-4.10)	(-3.08)	(-2.66)	(-1.72)
Treat*After	0.186	0.324	0.633**	0.937**
	(0.92)	(1.29)	(2.16)	(2.26)
After	0.081	0.153	-0.116	-0.109
	(0.59)	(0.83)	(-0.43)	(-0.35)
Weighted_Size		-0.022		0.030
		(-0.09)		(0.10)
Weighted_Q		-0.024		0.065
		(-0.19)		(0.50)
Weighted_Leverage		0.495		1.129
		(0.59)		(1.23)
Weighted_Intan		-0.050		-0.191
		(-0.31)		(-1.09)
Weighted_Freecashflow		0.813		0.112
		(0.85)		(0.09)
Weighted_ROA		0.890		0.787
		(1.15)		(0.75)
Constant	3.145***	3.650***	3.671***	4.429**
	(59.71)	(2.79)	(33.35)	(2.50)
Observations	368	313	368	313
R-squared	0.916	0.926	0.881	0.898
Deal FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes

Panel B: Falsification tests

	Patent Application		Patent Citation	
	(1)	(2)	(3)	(4)
Treat*After*HighacqAI*Hightardata	0.315	0.324	-0.028	0.132
	(1.55)	(1.55)	(-0.07)	(0.31)
Treat*After*HighacqAI	0.307	0.343	0.437	0.056
	(0.72)	(0.79)	(0.47)	(0.05)
Treat*After*Hightardata	-0.288	-0.225	0.223	0.292
	(-1.54)	(-1.08)	(0.63)	(0.76)
Treat*After	-0.201	-0.355	-0.710	-0.323
	(-0.49)	(-0.78)	(-0.78)	(-0.30)
After	0.273*	0.317*	0.253	0.014
	(1.81)	(2.02)	(0.76)	(0.05)
Weighted characteristics controls	Yes	Yes	Yes	Yes
Observations	368	313	368	313
R-squared	0.916	0.926	0.882	0.897
Deal FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes

Table 8. Post-Merger Performance of AI-Related Innovation

This table reports results for the treatment effect of a merger on post-merger AI-related innovations. Panel A presents regression results obtained by using a panel data set that, for each deal in the treatment sample (i.e., completed deals) and the control sample (i.e., bids withdrawn due to reasons exogenous to innovation), has observations running from five years prior to deal announcement to five years after deal announcement. The dependent variable is, in each year, the logarithm value of sum of the acquirer's and the target's AI-related innovation output measured by AI patent applications and citations, adjusted by SIC industry sector. Panel B presents the results from falsification tests when we assign pseudo announcement dates to our sample mergers. Definitions of all the variables are provided in the Appendix. All specifications include deal and year fixed effects. Robust *t*-statistics adjusted for deal-level clustering are reported in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Panel A: Post-merger AI-related innovation

	(1) AI Patent Application	(2) AI Patent Citation	(3) AI Patent Application	(4) AI Patent Citation
Treat*After*HighacqAI*Hightardata	0.880***	0.960***	0.955***	1.196***
	(4.82)	(3.71)	(5.61)	(4.66)
Treat*After*HighacqAI	-0.937***	-0.711**	-0.967***	-0.913**
	(-4.65)	(-2.24)	(-3.27)	(-2.23)
Treat*After*Hightardata	0.031	0.003	-0.048	-0.040
	(0.30)	(0.02)	(-0.32)	(-0.20)
Treat*After	0.343**	0.456*	0.461**	0.563**
	(2.09)	(1.87)	(2.13)	(2.20)
After	-0.216**	-0.369**	-0.361**	-0.445
	(-2.19)	(-2.36)	(-2.30)	(-1.71)
Weighted_Size			0.802**	0.721**
			(2.75)	(2.13)
Weighted_Q			-0.240*	-0.361*
			(-1.83)	(-2.05)
Weighted_Leverage			-0.186	0.385
			(-0.29)	(0.42)
Weighted_Intan			-0.442***	-0.505**
			(-2.86)	(-2.49)
Weighted_Freecashflow			-0.008	-0.786
			(-0.01)	(-0.43)
Weighted_ROA			0.314	0.520
			(0.43)	(0.52)
Constant	0.028	0.056	-3.196**	-1.866
	(0.68)	(0.94)	(-2.22)	(-0.94)
Observations	297	297	278	278
R-squared	0.724	0.570	0.753	0.608
Deal FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes

Panel B: Falsification tests

	(1) AI Patent Application	(2) AI Patent Citation	(3) AI Patent Application	(4) AI Patent Citation
Treat*After*HighacqAI*Hightardata	0.063	0.263	0.182	0.450
	(0.15)	(0.41)	(0.47)	(0.75)
Treat*After*HighacqAI	-0.357	-0.320	-0.362	-0.615
	(-1.00)	(-0.54)	(-0.96)	(-1.17)
Treat*After*Hightardata	0.274**	0.495**	0.244*	0.454**
	(2.22)	(2.49)	(1.87)	(2.28)
Treat*After	0.076	-0.155	0.335	0.459
	(0.30)	(-0.34)	(1.27)	(1.18)
After	0.095	0.297	0.052	0.082
	(0.79)	(1.33)	(0.30)	(0.33)
Weighted characteristics controls	Yes	Yes	Yes	Yes
Observations	297	297	278	278
R-squared	0.719	0.571	0.748	0.611
Deal FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes

Table 9. Subsample Test: The Role of Operating Performance

This table presents the results of CAR[-5,+5] regression on subsamples divided according to the median value of acquirers' ROA/ROE. Acquisitions with acquirers whose ROA/ROE is higher than the median fall into the high ROA/ROE group (columns (1) and (3)), and the rest fall into the low ROA/ROE group (columns (2) and (4)). All specifications control for the 6-digit SIC acquirer-industry sector fixed effects and year fixed effects. Robust *t*-statistics adjusted for firm-level clustering are reported in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

	CAR[-5,+5]			
	(1)	(2)	(3)	(4)
	High Acquirer ROA	Low Acquirer ROA	High Acquirer ROE	Low Acquirer ROE
LnacqAIskill	0.001	0.007***	0.001	0.007***
	(0.64)	(2.85)	(0.57)	(2.81)
Size	-0.011***	-0.028***	-0.011***	-0.029***
	(-3.75)	(-5.71)	(-3.78)	(-5.67)
Tobin's Q	0.006**	0.014***	0.007**	0.014***
	(2.25)	(3.56)	(2.38)	(3.56)
Leverage	0.032**	0.036	0.028**	0.037
	(2.41)	(1.17)	(2.14)	(1.16)
ROA	-0.052	0.051	-0.053	0.043
	(-0.79)	(1.06)	(-0.82)	(0.87)
Lnintan	0.005*	0.011***	0.005*	0.012***
	(1.91)	(3.15)	(1.95)	(3.15)
Freecashflow	-0.058	0.045	-0.055	0.054
	(-1.06)	(0.73)	(-1.04)	(0.84)
Tar_Hightech	-0.005	-0.008	-0.005	-0.009
	(-0.84)	(-1.07)	(-0.82)	(-1.12)
Allstockdeal	-0.034**	-0.002	-0.033*	-0.002
	(-2.04)	(-0.14)	(-1.94)	(-0.12)
Conglomerate	-0.003	-0.015**	-0.003	-0.014**
	(-0.76)	(-2.43)	(-0.78)	(-2.29)
Rel_Dealval	0.006***	0.005*	0.006***	0.005*
	(2.72)	(1.83)	(2.89)	(1.73)
Tenderoffer	-0.004	-0.016	-0.004	-0.015
	(-0.40)	(-0.91)	(-0.40)	(-0.84)
Constant	0.074***	0.116***	0.074***	0.118***
	(4.77)	(5.65)	(4.90)	(5.55)
Observations	1,894	1,910	1,969	1,832
R-squared	0.171	0.211	0.165	0.213
Acq. ind. FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes

Appendix

Table 1A: Definition of Variables

Variable Name	Definition
Acquirer-Target	An indicator variable which is equal to one if the firm pair ij is the real acquirer-target firm pair, and zero otherwise
AI Patent Application	The logarithm value of sum of AI patents applied for by the acquirer and the target for the period before the acquisition and the number of AI patents applied for by the combined firm for the period after the acquisition, minus industry (SIC) average number
AI Patent Citation	The logarithm value of sum of citation counts received by AI patents applied for by the acquirer and the target for the period before the acquisition and the citation counts received by AI patents applied for by the combined firm after the acquisition, minus industry (SIC) average number
Allstockdeal	Transaction Payment is stock only (SDC ofstock = 100)
Bothhighpatent	An indicator variable which is equal to one if both the acquirer and target's patent applications are above their respective medians, and zero otherwise
CAR[-3,+3]	Market model cumulative abnormal returns (CARs) over the [-3, +3] event windows surrounding the M&A announcement dates, where the parameters of the market model are estimated using the CRSP value-weighted index over [-180, -11] days relative to the acquisition announcement date
CAR[-5,+5]	Market model cumulative abnormal returns (CARs) over the [-5, +5] event windows surrounding the M&A announcement dates, where the parameters of the market model are estimated using the CRSP value-weighted index over [-180, -11] days relative to the acquisition announcement date
CAR[-10,+10]	Market model cumulative abnormal returns (CARs) over the [-10, +10] event windows surrounding the M&A announcement dates, where the parameters of the market model are estimated using the CRSP value-weighted index over [-180, -11] days relative to the acquisition announcement date
Patent Application	The logarithm value of sum of patents applied for by the acquirer and the target for the period before the acquisition and the number of patents applied for by the combined firm for the period after the acquisition
Patent Citation	The logarithm value of sum of citation counts received by patents applied for by the acquirer and the target for the period before the acquisition and the citation counts received by patents applied for by the combined firm after the acquisition
Conglomerate	An indicator variable which is equal to one if the acquirer and target are in the same industry (when they have the same 2-digit SIC code) , and zero otherwise
Diversifying	An indicator variable which is equal to one if the acquirer and target are not in the same industry (when they have different 2-digit NAICS code) , and zero otherwise
Freecashflow	Freecashflow =(oibdp-xint-txt-capx)/at of acquirer (for the year prior to deal announcement for deal-level regressions), with data from Compustat

HighacqAI	An indicator variable which is equal to one if the acquirer's Acq_AI Skill is above the median, and zero otherwise
Hightardata	An indicator variable which is equal to one if the target's DataIntense is above the median, and zero otherwise
Leverage	Leverage =(dlc+dltt)/at of acquirer (for the year prior to deal announcement for deal-level regressions), with data from Compustat
LnacqAIskill	log(Acq_AI Skill +1) , for the year prior to deal announcement in Table2-5. Acq_AI Skill is defined in Section 3.1
LnacqAIemp	log(Acq_AI Employee+1), for the year prior to deal announcement for deal-level regressions. Acq_AI Employee is defined in Section 3.1
Lnintan	log(intan) of acquirer (for the year prior to deal announcement for deal-level regressions), with data from Compustat
LntarAIskill	log(Tar_AI Skill +1). Tar_AI Skill is defined in Section 3.1
Rel_Dealval	log(valueoftransactionmil/sale), for the year prior to deal announcement for deal-level regressions, with data from Compustat
ROA	ni/at of acquirer (for the year prior to deal announcement for deal-level regressions) with data from Compustat
Salesgrowth	$Sales_t$-$Sales_{t-1}$ of acquirer (for the year prior to deal announcement for deal-level regressions) with data from Compustat
Samestate	An indicator variable which is equal to one if the acquirer and target are in the same state, and zero otherwise
Size	Log(me) and Log(at) of acquirer (for the year prior to deal announcement for deal-level regressions), where me= abs(PRC*SHROUT)/1000 from CRSP and at from Compustat
Tar_Freecashflow	Freecashflow =(oibdp-xint-txt-capx)/at of target (for the year prior to deal announcement for deal-level regressions), with data from Compustat
Tar_Leverage	Leverage =(dlc+dltt)/at of target (for the year prior to deal announcement for deal-level regressions), with data from Compustat
Tar_Hightech	An indicator variable which is equal to one if the target's 4-digit SIC is in: 3571, 3572, 3575, 3577, 3578, 3661, 3663, 3669, 3671, 3672, 3674, 3675, 3677, 3678, 3679, 3812, 3823, 3825, 3826, 3827, 3829, 3841, 3845, 4812, 4813, 4899, 7371, 7372, 7373, 7374, 7375, 7378, 7379, and zero otherwise.
Tar_Lnintan	log(intan) of target (for the year prior to deal announcement for deal-level regressions), with data from Compustat
Tar_ROA	ni/at of target (for the year prior to deal announcement for deal-level regressions) with data from Compustat
Tar_Salesgrowth	$Sales_t$-$Sales_{t-1}$ of target (for the year prior to deal announcement for deal-level regressions) with data from Compustat
Tar_Size	Log(at) of target (for the year prior to deal announcement for deal-level regressions), with data from Compustat
Tar_Tobin's Q	(at-ceq+prcc_f*csho)/at of target (for the year prior to deal announcement for deal-level regressions) with data from Compustat
Tenderoffer	An indicator variable which is equal to one if Tenderoffer="Yes" from SDC, and zero otherwise

Tobin's Q	(at-ceq+prcc_f*csho)/at of acquirer (for the year prior to deal announcement for deal-level regressions) with data from Compustat
Weighted_Freecashflow	The weighted average Freecashflow based on the acquirer's and target's total assets for the period before the acquisition; and the Freecashflow of the combined firm for the period after the acquisition
Weighted_Intan	The weighted average intan (in Compustat) based on the acquirer's and target's total assets for the period before the acquisition; and the Intan of the combined firm for the period after the acquisition
Weighted_Leverage	The weighted average Leverage based on the acquirer's and target's total assets for the period before the acquisition; and the Leverage of the combined firm for the period after the acquisition
Weighted_ROA	The weighted average ROA based on the acquirer's and target's total assets for the period before the acquisition; and the ROA of the combined firm for the period after the acquisition
Weighted_Size	The weighted average size based on the acquirer's and target's total assets for the period before the acquisition; and the size of the combined firm for the period after the acquisition
Weighted_Q	The weighted average Tobin's Q based on the acquirer's and target's total assets for the period before the acquisition; and the Tobin's Q of the combined firm for the period after the acquisition

Table A2: Post-merger innovation treatment sample criteria

Criteria	Treated Deals Left	Control Deals Left
They Involve innovative acquirers and target firms	436	48
They occur in acquirer-target industry pairs that match those of the withdrawn bids in the control sample	108	24
Their announcement year falls within a three-year window centered around the announcement year of the control bids to minimize time-related differences	82	18