When AI Acquires Data: Strategic Complementarities in M&A*

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Abstract

We examine how firms' artificial intelligence (AI) capabilities influence their mergers and acquisitions (M&A) decisions, using employees' job skills to measure AI strength. Firms with stronger AI capabilities are more likely to acquire data-rich targets and hire data analytics specialists, reflecting a strategic complementarity between AI expertise and data assets. Without paying higher acquisition premiums, these AI-intensive acquirers achieve superior M&A performance, especially when acquiring data-intensive targets. Such mergers lead to an increase in patents and AI-related patents, indicating greater innovation. Our findings highlight the combined power of AI and data as a key driver of M&A value and a force reshaping firm boundaries.

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

JEL Codes: G34, O14, O31, O33, M15, L25

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1 Introduction

Data is a critical asset that drives innovation, boosts productivity, and supports informed decision-making across sectors.[1] Its value, however, depends on how effectively it is combined with analytical capabilities. Firms with strong artificial intelligence (AI) skills are better positioned to extract value from data, while the development of AI models itself requires large amounts of training data that improve algorithmic performance and spur innovation (Beraja, Yang, and Yuchtman, 2023; Bartlett, McCrary, and O'Hara, 2025). AI and data therefore exhibit strong complementarities, leading AI-capable firms to acquire both internal and external data and, in doing so, reshape their organizational boundaries (Agrawal, Gans, and Goldfarb, 2019). This paper explores three key questions: How do corporate AI capabilities influence acquisition decisions? How valuable are data-intensive targets to firms with strong AI capabilities? And to what extent does alignment between AI expertise and data assets drive value creation in business combinations?

To address these questions, we measure firm-level AI capability using the prevalence of AI-related skills in the workforce. We first examine whether firms with stronger AI capabilities are more likely to merge with data-intensive targets.[2] An industry-level pairing analysis shows that mergers occur more frequently between firms operating in high-AI and high-data industries, providing evidence of AI–data complementarity. Second, using a framework similar to Bena and Li (2014), we analyze a sample of potential acquirer-target pairs and find that firms with strong AI capabilities are more likely to acquire data-rich targets. Conditional logit estimates confirm that strategic alignment between AI capabilities and data assets plays a key role in deal selection. Third, we examine firms' pursuit of data-related human capital. A pre-merger hiring analysis shows that high-AI acquirers increase recruitment of data analysts, particularly those skilled in both AI and data analytics, relative to industry peers. This pattern again signals AI firms' strategic focus on AI-data integration.

We next assess how AI capabilities, and their interaction with target data assets, af-

[1] See, for example, Begenau, Farboodi, and Veldkamp (2018), Zhu (2019), Brynjolfsson and McElheran (2019), Cong, Xie, and Zhang (2021), Goldstein, Spatt, and Ye (2021, 2025), He, Huang, and Zhou (2023).

[2] We measure firm-level AI capability using the prevalence of AI-related skills in the workforce, following Babina et al. (2024).

fect M&A performance. Announcement return regressions show that firms with stronger AI capabilities earn significantly higher cumulative abnormal returns (CARs) around deal announcements. These findings are robust to an instrumental variables approach that uses the share of AI graduates from nearby universities as an instrument for firm-level AI capability. Two-stage least squares (2SLS) estimates confirm a strong positive effect of AI capabilities on CARs.

We also find that acquisitions by high-AI firms generate greater combined wealth for both acquirer and target shareholders. The combined cumulative abnormal returns (*CombinedCAR*) increases with the acquirer's AI capability. Although target firms experience significantly higher announcement returns, high-AI acquirers capture a larger share of the anticipated synergies without paying higher acquisition premiums. Together, these findings suggest that AI capability enhances bargaining power in M&A negotiations.

To assess whether value creation stems from AI-data complementarity, we examine how acquirers' AI capabilities interact with target data intensity. The positive effects of AI are concentrated in acquisitions of data-rich firms. Mergers between high-AI acquirers and data-rich targets outperform all other combinations, whereas deals involving either high-AI acquirers and data-poor targets or low-AI acquirers and data-rich targets generate weaker returns. Overall, value creation is greatest when strong AI capabilities are paired substantial data assets.

We return to the question of why high-AI firms derive greater value from acquiring data-rich targets. Prior research suggests that AI promotes innovation by exploiting large datasets to uncover patterns and opportunities (Cockburn, Henderson, and Stern, 2019). We test this mechanism in the M&A context by examining post-merger innovation outcomes. High-AI acquirers of data-rich targets experience significant increases in both patent applications and citations, with particularly strong growth in AI-related patent applications for longer time window, which are especially data-intensive (Beraja, Yang, and Yuchtman, 2023). These findings indicate that combining AI capabilities with data-rich assets accelerates innovation.

Our study connects to several emerging research streams at the intersection of artificial intelligence (AI), data assets, and corporate finance. First, we build on prior work examining the economic role of data as an intangible asset. Recent studies conceptualize data as a productive, nonrival input that generates increasing returns through reuse and recombination (Jones and Tonetti, 2020; Farboodi and Veldkamp, 2021). This perspective extends the traditional theory of capital by highlighting that data, unlike physical assets, accumulates value through scale and variety rather than depreciation. Data's strategic importance has also been discussed in the context of information markets and privacy regulation (Bergemann and Bonatti, 2019; Goldfarb and Tucker, 2012; Agur, Ari, and Dell'Ariccia, 2025), where firms' ability to collect and process data shapes innovation potential, competitive advantage and firm entry (Begenau, Farboodi, and Veldkamp, 2018; Babina et al., 2025). Our paper contributes to this literature by showing that the value of data is conditional on firms' complementary AI capabilities. Rather than treating data as a stand-alone resource, we demonstrate that data assets yield greater returns when paired with analytical expertise capable of extracting insight and predictive value.

Second, we contribute to the literature on the implications of AI adoption for firm boundaries and human capital. The rise of AI and data-driven decision-making has blurred traditional firm boundaries by increasing the importance of intangible assets such as software, algorithms, and intellectual capital. Haskel and Westlake (2017) and Crouzet et al. (2022) emphasize that these intangibles, unlike tangible assets, create spillovers, scalability, and synergies that challenge conventional measures of firm value. Theoretical work on firm boundaries under technological change (Aghion and Holden, 2011; Rhodes-Kropf and Robinson, 2008) suggests that co-specialized intangibles, including knowledge and data, motivate boundary reconfiguration through mergers or alliances. Our results complement this view by identifying AI–data integration as a new form of intangible complementarity that drives acquisition behavior and post-merger performance.

Third, our work is related to the literature that discusses value creation through technology-driven mergers and acquisitions (Bena and Li, 2014). Our LinkedIn-based measure of AI capability draws from and contributes to the growing literature linking digital skills to firm performance (Babina et al., 2024; Eisfeldt, Schubert, and Zhang, 2026). Prior studies show that technology adoption depends critically on the supply and diffusion of specialized human capital (Deming and Noray, 2020; Gofman and Jin, 2022). Related work highlights that AI skill accumulation shapes labor market outcomes (Cao et al., 2024) and facilitates the reorganization of production toward knowledge-intensive tasks. Similarly, Ma, Ouimet, and Simintzi (2025) show that M&As act as catalyst for technology adoption, as technology-savvy acquirers take over targets that are less technologically sophisticated. Our paper relates to the literature that considers M&As as an important mechanism for transfer of technological knowledge from acquirers to targets. While Ma, Ouimet, and Simintzi (2025) show that technologically advanced acquirers implement more sophisticated technology at targets resulting in a decline of routine occupations at targets post merger, we show that AI-savvy acquirers improve their internal innovation capacity through strategically selecting data-rich targets. Thus, we highlight that AI capabilities influence strategic decisions such as target selection and post-merger integration. This perspective links the AI–data complementarity to the broader process of technological skill diffusion and workforce adaptation.

Fourth, a parallel body of work examines AI as a general-purpose technology that transforms productivity and innovation outcomes (Agrawal, Gans, and Goldfarb, 2019). Within corporate finance, AI has been shown to improve corporate governance (Erel et al., 2021), asset management (Sheng et al., 2024), and forecasting accuracy (Cao et al., 2024). Related evidence suggests that AI-related acquisitions can generate technological synergies and accelerate post-merger integration (Halvorsen, 2025), and that firms could merge assets to exploit synergies (Hoberg and Phillips, 2010). Our findings extend this literature by identifying "AI–data synergy" as a distinct mechanism of value creation in M&A. We show that the positive performance effects of AI-capable acquirers are amplified when targets possess rich data assets, consistent with theories of co-specialized intangible capital.

Finally, our analysis relates to research on data governance and privacy regulation, which shape firms' incentives to collect and utilize data (Jamal, Maier, and Sunder, 2003; Carrière-Swallow and Haksar, 2019). Data-rich acquisitions may expose firms to heightened regulatory risk, particularly under regimes such as General Data Protection Regulation (GDPR) or California Consumer Privacy Act (CCPA). By interpreting Item 1A risk disclosures as indicators of data intensity, our framework captures how firms internally recognize these governance challenges. Our evidence thus complements studies emphasizing the tension between data privacy, innovation, and market efficiency (Goldfarb and Tucker, 2012; Agur, Ari, and Dell'Ariccia, 2025; Acemoglu and Restrepo, 2019).

Taken together, our paper contributes to a rapidly evolving literature on the economics of AI and data. We integrate insights from the theory of intangible capital, labor skill diffusion, and digital innovation to propose and test the notion of strategic AI–data complementarities in M&A. In doing so, we highlight a new channel through which AI reshapes firm boundaries, value creation, and post-merger innovation in the modern data economy.

2 Data and Variables

We construct our sample using the SDC Platinum database and focus on U.S. acquisitions announced between January 1, 2009, and December 31, 2019. Following Masulis, Wang, and Xie (2007) and Gokkaya, Liu, and Stulz (2023), we apply the following filters: (1) the target is a U.S. firm; (2) the acquirer holds less than 50% of the target prior to the deal and at least 50% afterward; (3) the disclosed deal value exceeds $1 million and represents at least 1% of the acquirer's market capitalization, measured 11 trading days before the announcement; (4) the transaction is neither an intended deal[3] nor a remaining interest acquisition; and (5) the acquirer does not operate in the finance, insurance and real estate sector, as defined by SIC codes. After applying these filters, the SDC sample contains 5,378 unique transactions with complete deal information, including announcement dates, deal values, payment methods, and acquirer ownership. We then merge the filtered SDC transactions with Compustat and CRSP data.[4] Compustat supplies firm-level financial variables, and CRSP daily returns are used to compute cumulative abnormal returns (CARs).

[3]The acquirer has announced that they propose or expect to make an acquisition, generally used for repurchases, as defined in SDC.

[4]We use the updated SDC-Compustat matching provided by Michael Ewens `https://github.com/michaelewens/SDC-to-Compustat-Mapping`. For details, see Ewens, Peters, and Wang (2025), Phillips and Zhdanov (2013).

2.1 Measuring AI Capabilities of Firms

Given the central role of human capital in deploying AI systems, we measure firms' AI capabilities based on the prevalence of AI-related skills in their workforce, using LinkedIn data, the largest professional networking platform, with 169.9 million U.S. users in 2019. The dataset includes self-reported information on education (institutions, fields of study, attendance periods), work experience (employers, titles, dates), skills, and other relevant attributes. We match acquirers and targets to LinkedIn data in two steps. First, we use company website URLs from Compustat as primary identifiers to link firms with LinkedIn profiles. For missing URLs, we supplement with manual web searches. Remaining unmatched firms are hand-matched using name, location, founding year, and industry, achieving an overall match rate of approximately 80%.

For matched firms, we construct firm-year AI capability measures using employee profile data. AI-related skills are identified using the taxonomy developed by Babina et al. (2024), which includes 67 items such as *Deep Learning*, *XGBoost*, *NLP*, and *Machine Learning*.[5] An employee is classified as an AI employee if they report at least one AI-related skill. For example, someone listing both *Deep Learning* and *XGboost* is counted as one AI employee with two AI skills.

We track AI employees and skills monthly, aggregating across employees and months to construct firm-level measures of total employees, AI employees, and AI skills. For each acquirer and target firm, we compute average monthly values over the 12 months preceding the deal announcement, generating measures for average monthly employees ($Acq\_Employee$ and $Tar\_Employee$), AI employees ($Acq\_AIEmployee$ and $Tar\_AIEmployee$), and AI skills ($Acq\_AISkill$ and $Tar\_AISkill$). For each transaction, *Acq_AISkill* denotes the number of AI skills, and *Acq_AIEmployee* indicates the number of AI employees at the acquirer in the year before the M&A announcement. Target firm measures are constructed analogously. After excluding observations with missing values, the final sample comprises 4,464 unique transactions, based on 13,263,435 employment records from 8,521,432 LinkedIn individual profiles.

[5] The taxonomy was systematically developed to capture the most relevant AI skills on LinkedIn.

— Figure 1 about here —

Figure 1 maps the geographical distribution of AI talent across U.S. counties, based on LinkedIn work location data. We geolocate AI skills and aggregate them at the county level. The resulting heatmap shows strong concentrations in established tech hubs and university centers such as the San Francisco Bay Area, Seattle, Boston, New York City, Austin, Denver, and Washington D.C., closely mirroring patterns in the geography of tech labor markets and supporting the validity of our LinkedIn-based AI measures.

2.2 Measuring Data Intensity

We develop a novel measure of data intensity based on the frequency of data security-related keywords in Item 1A risk disclosures from firms' 10-K filings. This approach is grounded in the idea that firms handling large or complex datasets face greater data security risks due to the need to protect sensitive information, comply with evolving regulations on handling data (e.g., GDPR, CCPA), and mitigate potential breach-related costs. Ramadorai, Uettwiller, and Walther (2025) show that as these regulations have become more binding, firms' data privacy disclosures have become more detailed and truthful. As data volumes increase, so does exposure to these risks, making the extent of data security disclosures a useful proxy for data intensity.

To construct this measure, we compile a list of data security keywords from the Cloud Security Alliance's *Data Security Glossary*, a widely recognized standard in cloud and cybersecurity. Using Python, we count the occurrences of these keywords in item 1A risk-factor disclosures, where firms are required to report material risks, including cybersecurity threats. Our data intensity measure, *DataIntensity*, is defined as the total count of these data risk keywords in a firm's disclosure. This measure captures the emphasis placed on data-related risks and serves as a proxy for the scale and complexity of the firm's data assets.

For robustness, we construct an alternative measure of data intensity using a large language model. Following Eisfeldt, Schubert, and Zhang (2026), we use GPT-4.1 to analyze the business descriptions in target firms' 10-K filings and assess their potential access to data. Specifically, the model evaluates the extent to which each annual report addresses six data-related dimensions: (i) the general nature of the business, (ii) firm scale and reach, (iii) data collection mechanisms, (iv) data utilization practices, (v) data infrastructure and management, and (vi) data regulation and privacy. Based on this assessment, the model assigns an overall score that quantifies the firm's data assets.

2.3 Other Variables

We follow standard M&A event study methodology to estimate acquirer cumulative abnormal returns (CARs). The market model is estimated over a [-240, -11] trading-day window preceding the deal announcement. The event window spans [-3,+3] days around the announcement date. Abnormal returns (ARs) are calculated as the difference between actual and predicted returns, and CARs are the cumulative sum of ARs over the event window. To assess robustness, we also test alternative event windows: [-4, +4] and [-5, +5].

Deal-specific innovation outcomes are measured using firm-level patent data from the Extended KPSS dataset (Kogan et al., 2017). We define *Patent Application* as the sum of patents applied for by the acquirer and the target in the five years before the acquisition, and the number of patents applied for by the combined firm in the five years after. *Patent Citation* is constructed analogously using forward citation counts. To examine AI-related innovation, we use the Artificial Intelligence Patent Dataset (AIPD)[6] and match patents to firms via the USPTO PatentsView Dataset and Google Patents Public datasets. *AI Patent Application* is defined as the sum of AI patents applied for by the acquirer and the target pre-acquisition, and the number applied for by the combined firm post-acquisition. Patents are classified as AI-related if *predict93_any_ai* provided by AIPD equals one. The variable *predict93_any_ai* takes a value of 1 if the patent was predicted to be AI patent in any of the technology component models based on the highest 93% threshold and 0 otherwise (Pairolero et al., 2025; Giczy, Pairolero, and Toole, 2022). These measures capture both the quantity and quality of innovation surrounding each deal.

Our empirical models include a comprehensive set of control variables. At the

[6]Developed by the USPTO's Office of the Chief Economist, the AIPD uses machine learning models to identify AI-related patents and pre-grant publications in U.S. patents from 1976–2023 (Pairolero et al., 2025).

firm level, we control for firm size, Tobin's Q, leverage, ROA, intangible asset ratio, and R&D expense, as well as the target's status (public or private). Deal-level controls include payment method (*AllStock*), relative deal value (*Rel_DealVal*), challenged deal indicator (*Challenge*), cross-border indicator (*Crossbor*), diversification (*Conglomerate*), and whether acquirer and target are both in high technology industry (*Hightechdeal*), defined following Loughran and Ritter (2004) and Li et al. (2018)). Detailed variable definitions are provided in Appendix A.

2.4 Summary Statistics

Table 1 reports summary statistics in five panels. Panel A reports statistics for acquiring firms. The average acquirer employs approximately 1,456 workers; however, firm size is highly skewed, with largest acquirers employing more than 80,000 individuals. On average, acquirers employ about 23 AI-skilled workers and report 32 AI-related skills, although the large standard deviations indicate substantial heterogeneity in AI capabilities across firms.[7] The log-transformed AI measures, $LnAcqAIEmp$ and $LnAcqAISkill$, have means of 1.28 and 1.38, respectively. Acquirers exhibit moderate leverage, with a mean of 0.26, and hold a sizable proportion of intangible assets, with an average intangible ratio of 0.28. R&D intensity averages 3%, while profitability, measured by ROA, is modest at 2% on average. The mean Tobin's Q is 2.00, indicating relatively strong growth opportunities among acquiring firms.

Panel B reports statistics for target firms. Targets are substantially smaller than acquirers, with an average of 291 employees. AI capability among targets is limited relative to acquirers: the average target employs fewer than four AI-skilled workers and reports fewer than five AI-related skills. The mean $LnTarAISkill$ is 0.48. Approximately 16% of targets are publicly listed. Measures of data intensity, available for a subsample of targets, display considerable dispersion. The mean value of the continuous data-intensity measure is 385, while roughly one-third are classified as high-data-intensity firms. Alternate GPT-based measures yield similar classifications, with 40% of targets classified as

[7] Employment is recorded monthly, and annual averages are reported for the year preceding the transaction.

high data intensity. Overall, these figures suggest that acquirers are larger and possess stronger AI-related human capital, consistent with evidence that larger firms have better access to financing and greater capacity to invest in proprietary technologies (Archer and Faerber, 1966; Kahle and Stulz, 2013; De Guevara, Maudos, and Salvador, 2022).

— Table 1 about here —

Panel C describes transaction features. Only 4.0% of deals are financed entirely with stock, and challenged transactions are rare, accounting for about 1% of the sample. Approximately 39% of transactions are conglomerate mergers, while 5% involve cross-border acquisitions. The average relative deal value is 0.25, indicating that the typical transaction represents one-quarter of the acquirer's market capitalization. High technology deals account for 21% of the sample, where both acquirers and targets operate in high tech industries. Acquirer announcement returns are positive on average: mean CARs equal 1% across the [-3,+3], [-4,+4], and [-5,+5] event windows, with substantial dispersion. For the subsample with available target return data, targets experience large positive announcement effects, with mean CARs of 14% over both [-2,+2] and [-3,+3] windows. Combined announcement returns average 3%. The acquirer's share of total synergy is close to zero on average, while there is considerable variation in value appropriation across deals.

Panel D summarizes post-merger innovation outcomes. In the subsample with patent data, combined firms file an average of 35 AI-related patent applications and 102 total patent applications, with citation counts averaging 405. The large standard deviations indicate substantial heterogeneity in innovative activity across merged entities.

Panel E reports worker-level measures constructed from matched SDC-LinkedIn data. Employees' tenure averages approximately 58 months at acquiring firms and 57 months at target firms, indicating similar experience distributions across the two groups. The average employee reports very few AI-related skills (a mean of 0.03, with more than 98% reporting none), reflecting the scarcity of specialized AI expertise in the broader workforce. This scarcity creates a strategic opportunity: firms that invest in AI-related human capital can develop a distinctive advantage in managing large-scale data assets and realizing synergies–an advantage that smaller, data-rich firms may find difficult to replicate.

3 Empirical Results

3.1 The Pursuit of Data by High-AI Acquirers

3.1.1 Industry distribution of merger pairing

We test whether AI–data complementarity drives M&A activity by examining whether firms with stronger AI capabilities are more likely to acquire data-intensive targets. Figure 2 analyzes merger frequency using an industry-level pairing approach based on SDC industry classifications. We retain the 15 acquirer industries and 15 target industries with the highest merger frequencies, ranked by acquirer AI capability and target data intensity, respectively. Merger propensity is measured by the number of deals for each acquirer-target industry pair. The vertical axis ranks acquirer industries by AI capability, decreasing from top to bottom, while the horizontal axis ranks target industries by data intensity, decreasing from left to right.

— Figure 2 about here —

The figure reveals a clear pattern linking AI capability and data intensity to M&A activity. Merger activity is concentrated in the upper-left region of the matrix, where high-AI acquirer industries pair with high data-intensity target industries. Darker cells (i.e., larger counts) in this region indicate that firm with strong AI capabilities disproportionately acquire data-rich targets, consistent with AI-data complementarity rather than random industry matching.

Although many deals occur within the same industry, reflecting the well-known tendency toward within-industry consolidation, there is substantial cross-industry activity. This is especially pronounced among high-AI acquirers, whose cross-industry mergers are likely to involve data-intensive targets, suggesting strategic motives beyond industry consolidation.

We also observe a pronounced asymmetry between high- and low-AI acquirers. Firms in high-AI industries engage in acquisitions across a broad range of target industries, particularly those with high data intensity. In contrast, low-AI acquirers complete fewer deals overall, and their activity is more evenly distributed or concentrated in low-data-intensity targets. This asymmetry suggests that AI capability expands the set of feasible and attractive acquisition targets. Consistent with this interpretation, data-intensive industries such as software, business services, and telecommunications attract a disproportionate share of acquisitions by AI-intensive acquirers.

Overall, the figure provides visual evidence that M&A activity is systematically structured around AI-data complementarities. Firms with strong AI capabilities are significantly more likely to acquire data-intensive targets, both within and across industries, supporting the view that AI talent and data assets jointly shape strategic merger decisions rather than mergers being driven solely by traditional industry consolidation motives.

3.1.2 Firm-level analysis of merger pairing

To formally examine the strategic pairing of AI-capable acquirers with data-rich targets, we estimate a firm-level selection model. Our central hypothesis is that firms with stronger AI capabilities are more likely to acquire targets with substantial data assets. We test this hypothesis using a conditional logit framework following Bena and Li (2014), which compares realized acquirer-target pairs with matched counterfactual pairs.

We construct three control samples, each defining a set of plausible alternative acquirers or targets for the firms involved in observed deals. For each actual acquirer or target, we identify up to five matched hypothetical firms, generating a set of potential merger combinations. We then pool realized and hypothetical pairs to examine which firm characteristics predict observed M&A matches. Control firms are drawn from Compustat/CRSP as of the fiscal year-end preceding the deal announcement and must not have participated in any M&A activity, either as acquirers or targets, during the prior three years.

The first control group matches firms on industry and size, capturing the well-documented clustering of M&A activity within industries (Andrade, Mitchell, and Stafford, 2001; Harford, 2005). For each actual acquirer or target, we identify up to five matching firms based on the SIC industry classification and total assets. Industry matching begins at the four-digit SIC level and is progressively broadened to the three- and two-digit levels if fewer than five peers are available.[8] Within the matched industry pool, we select the five firms with the smallest size differences relative to the actual firm. Firm size is measured by total assets at the fiscal year-end preceding the deal announcement. We refer to these firms as the *Industry-Size-Matched* controls.

The second control group further conditions on operating performance by incorporating return on assets (ROA), a key determinant of M&A activity (Healy, Palepu, and Ruback, 1992). Using propensity-score matching, we estimate a probit model with firm size and ROA as predictors and match each actual firm to the five nearest neighbors from the industry-matched pool.

The third and most stringent control group additionally incorporates Tobin's Q to account for differences in growth opportunities, valuation, and strategic fit—factors known to influence merger decisions (Andrade, Mitchell, and Stafford, 2001; Shleifer and Vishny, 2003; Rhodes-Kropf and Viswanathan, 2004; Rhodes-Kropf and Robinson, 2008). Tobin's Q is added to the propensity-score model used in the second control group, and the five nearest firms from the industry-matched pool are selected as control firms.

Following sample construction, we estimate the following model:

$$\begin{aligned} Acquirer\text{-}Target_{ijm} = {} & \alpha + \beta_1 HighAcqAI_{im} \times HighTarData_{jm} \\ & + \beta_2 LowAcqAI_{im} + \beta_3 LowTarData_{jm} \\ & + \beta_4 Acquirer\ Characteristics_{im} \\ & + \beta_5 Target\ Characteristics_{jm} \\ & + \beta_6 Deal\ Characteristics_{ijm} \\ & + Deal\ Group\ FE_m + \varepsilon_{ijm}, \end{aligned} \tag{1}$$

where i and j index acquirers and targets, respectively, and ij denotes all possible acquirer-target pairings within deal m. The dependent variable, $Acquirer\text{-}Target_{ijm}$, equals one for realized matches and zero for hypothetical pairs. Control variables include firm fun-

[8] Deals without at least five peers at the two-digit SIC level are excluded.

damentals (size, Tobin's Q, leverage, ROA, sales growth, and R&D expense), as well as indicators for same-state location and cross-industry deals. The analysis is restricted to transactions in which both acquirer and target are publicly traded.

We estimate equation (1) using three matched samples: *Industry-Size-Matched, Industry-Size-ROA-Matched* and *Industry-Size-ROA-Tobin's Q-Matched*. In each sample, every target is paired with up to five matched hypothetical acquirers, and every acquirer is paired with up to five matched hypothetical targets. We retain only deal groups with at least three pseudo-acquirers and three pseudo-targets. The resulting samples include 531, 514, and 507 realized deals, respectively, and, when combined with matched controls, each sample contains more than 4,000 observations.

— Table 2 about here —

Table 2 reports conditional logit estimates of the acquirer-target pairing model across three increasingly stringent matched samples. Across all three specifications, the interaction between high acquirer AI capability and high target data intensity is positive and statistically significant. The coefficient on *HighAcqAI* × *HighTarData* ranges from 0.61 to 0.72 and is significant at the 5% level in every column. This indicates that, conditional on deal fixed effects and firm characteristics, AI-capable acquirers are significantly more likely to match with data-intensive targets than with otherwise similar firms. The stability of the coefficient across the industry-size, industry-size-ROA, and industry-size-ROA-Tobin's Q matched samples suggest that this effect is not driven by differences in firm scale, operating performance, or growth opportunities, but instead reflects a genuine strategic complementarity between AI capabilities and data assets.

In contrast, the main effects of $HighAcqAI$ and $HighTarData$ are either negative or insignificant. High-AI acquirers are significantly less likely to match with a generic target in the absence of high data intensity, as reflected in the large and negative coefficients on $HighAcqAI$. Similarly, $HighTarData$ on its own is not a strong predictor of being acquired. Together, these patterns indicate that AI capability and data intensity are not independently attractive in the matching process; rather, their value arises primarily through their interaction. This reinforces the interpretation that M&A decisions are driven by complementarities rather than by standalone firm attributes.

Overall, the results provide strong firm-level evidence that M&A activity is systematically organized around AI–data complementarities. AI-capable acquirers are significantly more likely to select data-rich targets, and this pattern is robust to increasingly strict matching criteria and a rich set of firm and deal controls.

3.1.3 Supplementary evidence on human capital

To examine AI-data complementarity, we analyze changes in acquirers' workforce composition before and after the transaction, with a focus on data analytics roles. We expect AI-intensive firms to proactively invest in data-related human capital prior to acquiring data-rich targets, thereby strengthening their ability to integrate and extract value post-acquisition. To test this hypothesis, we examine whether high-AI firms exhibit stronger demand for data-oriented roles, such as *data analysts* and *data scientists*, identified by job titles containing the keyword "data" (e.g., "senior data analyst") in the years leading up to acquisitions. We construct two measures: (i) the total number of data analysts and (ii) the subset of data analysts who also report at least one AI-related skill, as defined above. These measures capture firms' strategic efforts to integrate AI and data capabilities through talent acquisition.

— Figure 3 about here —

Figure 3 plots hiring trends for data analysts (industry-adjusted) over a 13-year window [-10, +2] around deal announcements (year 0), comparing high-AI and low-AI acquirers. The two panels provide complementary evidence on how AI-intensive firms build human capital to support AI–data complementarity, both before and after acquisitions.

Panel A shows a clear and persistent divergence between high-AI and low-AI acquirers in industry-adjusted hiring of data analysts over a long horizon around deal year. High-AI acquirers exhibit a steady upward trend in data-analyst employment beginning many years before the transaction, indicating a gradual and deliberate buildup of data-related human capital. Importantly, these patterns emerge well before the deal year (year

0), which suggests that data-analytics hiring is not a short-term response to an impending acquisition, but rather part of a longer-term strategic investment by AI-intensive firms.

The absence of a sharp break at the deal year further reinforces this interpretation. Instead of a discrete post-merger spile, hiring continues smoothly through and after the acquisition, consistent with the view that data capabilities are treated as a durable organizational asset.

Panel B focuses on data analysts who also possess AI-related skills. The divergence between high-AI and low-AI acquirers is even more pronounced here. High-AI acquirers steadily increase employment of workers with combined AI and data expertise, while low-AI acquirers show a persistent and accelerating decline. This pattern indicates that high-AI firms are not expanding merely generic data functions; they are specifically investing in talent that directly complements AI development, such as model training, feature engineering, and advanced analytics. It suggests that AI-intensive firms strategically target hybrid skill sets that enable effective use of large-scale data in AI applications, rather than relying on traditional data roles alone.

Taken together, the figures provide strong supplementary evidence for AI-data complementarity at the human-capital level. High-AI acquirers systematically build and maintain data-oriented, especially AI-enabled data talent well before acquisitions, positioning themselves to integrate and exploit data-intensive targets more effectively.

3.2 Acquirer AI and Announcement Returns

3.2.1 Baseline result

Building on the evidence that AI capabilities and data assets are strategically aligned in M&A decisions, we next examine whether this alignment generates measurable market value. Specifically, we assess how acquirers' AI capabilities affect cumulative abnormal returns (CARs) around deal announcements.

$$\begin{aligned} CARs_{i,t} = \alpha &+ \beta_1 AcquirerAI_{i,t-1} + \beta_2 AcquirerControls_{i,t-1} \\ &+ \beta_3 TargetControl_{i,t-1} + \beta_4 DealControls_{i,t} + AcquirerIndustryFE \\ &+ YearFE + AcquirerState \times YearFE + \varepsilon_{i,t}. \end{aligned} \tag{2}$$

The key independent variable, $AcquirerAI$, measures the acquirer's AI capability in the year preceding the deal announcement. We proxy for AI capability using two log-transformed variables: $LnAcqAISkill$, which captures the average number of AI skills, and $LnAcqAIEmp$, which measures the average number of AI-skilled employees.

Following the M&A literature, we control for firm fundamentals, including size, Tobin's Q, leverage, ROA, intangible asset ratio, and R&D expense, as well as the target's status (public or private). Deal characteristics include payment method, relative deal value, challenged deal, cross-border transaction, diversifying merger, and whether both firms operate in high technology industries. Regressions further include fixed effects for acquirer industry (four-digit SIC), year, and acquirer state $\times$ year.

— Table 3 about here —

Table 3 reports announcement return regressions linking acquirer AI capabilities to short-window stock market reactions around M&A announcements. Columns (1)–(3) examine AI skill intensity, measured as the log of acquirer AI skill. The coefficients on *LnAcqAISkill* are positive and highly statistically significant across all three event windows. A one-standard-deviation increase in AI capability increases CAR [-3,+3] by 0.795 percentage points, corresponding to approximately 79.5% of the sample mean. The magnitude remains stable as the event window expands from [-3,+3] to [-5,+5]. This indicates that markets view acquisitions by AI-capable firms more favorably consistent with expectations of greater synergy realization.

Columns (4)–(6) use an alternative measure of AI capability – the log number of AI-skilled employees – and yields nearly identical results. The coefficients on $LnAcqAIEmp$ are positive and significant at the 5% or 1% level across all windows, confirming that the positive announcement effects are not driven by a particular measurement of AI capability. The consistency across both skills and headcount-based measures strengthen the interpretation that AI human capital is value relevant in M&A.

Overall, the results show that acquirer AI capability is positively priced by financial markets at the time of deal announcements. Investors appear to expect that AI-intensive firms generate higher synergies or better integrate acquisitions, reinforcing the view that

AI human capital is a strategic asset that enhances value creation in M&A.

3.2.2 Instrumental variable approach

A potential concern with the CAR results is that firms with stronger AI capabilities may simply be better acquirers, generating higher returns independent of AI. To address this concern, we implement an instrumental variable (IV) strategy following Babina et al. (2024), exploiting exogenous variation is firms' access to local AI talent. This approach leverages regional labor market conditions that affect AI skill acquisition but are plausibly unrelated to firm-specific acquisition quality.

We construct a distance-based instrument that captures firm-level exposure to local AI talent supply, measured as the share of AI graduates from nearby universities, weighted by university size. The IV is constructed in three steps. First, using data from Babina et al. (2024), we identify "AI-strong" universities, those in the top 3% by AI researcher count during 2006-2008, a pre-sample period that ensures exogeneity to subsequent firm behavior. Second, we measure each firm's geographic proximity to these universities using NBER county-level distance data, restricting attention to universities located within a 100-mile radius of the firm's headquarter to capture localized labor-market effects. Third, we compute a size-weighted average of AI graduates from these nearby universities. Formally, the instrument is defined as:

$$IV_{i,t} = \sum_{j \in J_{it}} \frac{AI\_Grads_{jt}}{Total\_Grads_{jt}} \times Weight\_Size_{jt}, \tag{3}$$

where AI_Grads_{jt} is the number of AI-related first-job graduates from university *j* in year *t*, $Total\_Grads_{jt}$ is the total number of graduates from university j in year t, and J_{it} is the set of AI-strong universities whose counties are located within a 100-mile radius of the county where the firm *i*'s headquarters are situated. The weight term ($Weight\_Size_{jt}$) reflects university size:

$$Weight\_Size_{jt} = \frac{\ln(Total\_Grads_{jt})}{\sum_{k \in \text{100-mile radius}} \ln(Total\_Grads_{jkt})} \tag{4}$$

This instrument captures firm-level exposure to exogenous variation in local AI talent supply. We assign the instrument in the deal-announcement year to ensure relevance for predicting acquirer AI capability in the first stage. The first-stage regression is:

$$\begin{aligned} LnAcqAISkill_{i,t-1} = \beta_0 + \beta_1 IV_{i,t} + \beta_2 AcquirerControls_{i,t-1} + \beta_3 TargetControl_{i,t-1} \\ + \beta_4 DealControls_{i,t} + AcquirerIndustryFE \\ + YearFE + AcquirerState \times YearFE + \nu_{i,t} \end{aligned} \tag{5}$$

The predicted values from the first stage are then used in the second-stage to estimate the causal effect of AI capability on acquisition performance:

$$\begin{aligned} CARs_{i,t} = \alpha + \beta_1 Ln\widehat{acqAI}skill_{i,t-1} + \beta_2 AcquirerControls_{i,t-1} \\ + \beta_3 TargetControl_{i,t-1} + \beta_4 DealControls_{i,t} \\ + AcquirerIndustryFE + YearFE + AcquirerState \times YearFE + \varepsilon_{i,t} \end{aligned} \tag{6}$$

By exploiting exogenous variation in local AI talent supply, this two-stage least squares (2SLS) approach strengthens identification and isolates the causal effect of AI capability on acquisition performance, mitigating concerns that high-AI firms are inherently superior acquirers rather than benefiting specifically from AI capabilities.

— Table 4 about here —

Table 4 reports the instrumental variable results linking acquirer AI capability to announcement returns. Column (1) presents the first-stage regressions. The local AI talent instrument is strongly positively related to *LnAcqAISkill*, with a large and highly significant coefficient. The first-stage F-statistics of 34.69 comfortably exceeds conventional thresholds, alleviating concerns about weak instruments and confirming that local AI talent supply is a powerful predictor of firm-level AI capability. This finding is consistent with the idea that geographic exposure to AI-skilled labor meaningfully shapes firms' AI investments.

Column (2)-(4) report the second-stage 2SLS estimates for CARs over the [-3,+3], [-4,+4], and [-5,+5] event windows. Across all specifications, the coefficient on the instrumented *LnAcqAISkill* is positive and statistically significant, with magnitudes that increase as the event window widens. These estimates imply that higher AI capability causally increases announcement returns, indicating that markets view acquisitions by AI-capable firms as value-enhancing.

The control variables behave largely as expected. Firm size enters negatively and significantly, consistent with the well-documented tendency for larger acquirers to experience lower announcement returns. Leverage and profitability (ROA) are positively associated with CARs, indicating that financially stronger acquirers generate more favorable market reactions. Target public status is also negatively related to announcement returns, consistent with greater competition and lower surplus capture in acquisitions of publicly traded targets.

Overall, the IV results reinforce the main conclusion of the paper: acquirer AI capability has a positive and causal effect on acquisition performance. By exploiting exogenous variation in local AI talent supply, this approach mitigates concerns that AI-intensive firms are simply better acquirers for unrelated reasons, strengthening the interpretation that AI capabilities themselves drive superior M&A outcomes.

3.2.3 Combined Wealth Effects and Acquisition Premium

We next investigate whether high-AI acquirers enhance the total value of merged firms by generating greater combined wealth effects. Examining both acquirer and target returns allows us to capture overall value creation associated with acquirers' AI capability. The caveat is that this analysis can only be done for the subsample of targets that are also publicly traded.

To measure the combined wealth effect, we construct *CombinedCAR* as the market-capitalization-weighted average of the target's CAR over [-41, +3] and the acquirer's CAR over [-3, +3], using market capitalization from day -42 (target) and day -4 (acquirer) as weights (Dessaint, Eckbo, and Golubov, 2025). We then re-estimate our baseline CAR regression with *CombinedCAR* as the dependent variable.

— Table 5 about here —

Table 5 examines how acquirer AI capability affects the total value created by mergers, how that value is divided between acquirers and targets, and target announcement returns for deals involving public targets. The results indicate that acquirer AI capability increases overall merger synergies and shifts a larger share of gains toward acquirers, while also benefiting target shareholders.

Column (1) shows that *LnAcqAISkill* is positive and significantly associated with *CombinedCAR*, indicating that mergers undertaken by more AI-capable acquirers generate greater total value for the combined firm. Column (2) shows no significant effect of *LnAcqAISkill* on *Premium*, indicating that AI-capable acquirers do not systematically pay higher premiums to target shareholders.[9] Column (3) further shows a positive and marginally significant effect of *LnAcqAISkill* on the acquirer's share of synergy gains, implying that AI-capable acquirers capture a larger fraction of the value they create. Together, these results indicate that AI-capability improves bargaining position, allowing acquirers to retain more of the synergies without transferring them to targets through higher premia.

Column (4) and (5) show that target CARs are significantly higher when the acquirers have stronger AI capabilities. This suggests that, despite not receiving higher premia on average, target shareholders still benefit from being acquired by AI-capable firms, potentially reflecting expectations of higher long-term value creation.

Taken together, the results show that acquirer AI capability enhances total merger value and allows acquirers to appropriate a larger share of the resulting synergies, while still generating positive announcement effects for targets. These findings reinforce the view that AI capability is a source of real economic value in M&A, improving both value creation and value capture rather than merely redistributing gains.

[9] Premium is measured as the dollar premium paid to target scaled by the sum of the acquirer's and target's market capitalizations on days -4 and -42, respectively (Dessaint, Eckbo, and Golubov, 2025). The dollar premium is calculated as the target's CAR over [-41, +3] multiplied by its market capitalization on day -42.

3.2.4 AI-Data Complementarity and Value Creation in Mergers

In AI-driven firms, value creation critically depends on the effective use of large-scale data for insight generation. Our earlier analyses of industry pairing, firm-level matching, and data analyst hiring highlight a strong strategic complementarity between AI capability and data resources. We now examine whether mergers that pair high-AI acquirers with data-intensive targets generate greater shareholder value than other acquirer-target combinations.

As discussed above, we measure target data intensity using the frequency of data security-related keywords in Item 1A of firms' 10-K filings, classifying targets as high-data (*HighTarData*) or low-data (*LowTarData*) based on the sample median.[10] Acquirers and targets are similarly classified as high-AI (*HighAcqAI*/*HighTarAI*) or low-AI (*LowAcqAI*/*LowTarAI*) using their respective sample medians. This classification yields eight (2$\times$4) possible deal combinations based on acquirer AI, target AI, and target data intensity, allowing us to evaluate whether value creation stems from pairing AI-capable acquirers with data-rich targets.

Table 6 reports announcement return regressions that test whether value creation in M&A depends on the joint presence of acquirer AI capability and target data intensity. The results provide clear evidence that announcement gains are concentrated in transactions that combine high AI capability on the acquirer side with data-rich targets.

Across all three event windows, the interaction $HighAcqAI \times HighTarData$ is positive and statistically significant. The estimated effects are economically meaningful and stable as the event window expands from [-3,+3] to [-5,+5], indicating that investors respond favorably when AI-capable acquirers purchase data-intensive targets. This pattern is consistent with AI-data complementarity; markets expect such combinations to generate superior synergies by enabling acquirers to more effectively exploit acquired data assets.

By contrast, other acquirer-target combinations do not produce comparable gains. Deals in which high-AI acquirers acquire low-data targets (*HighAcqAI* $\times$ *LowTarData*) yield

[10] Internet Appendix Table IA reports qualitatively similar results when we use our alternative ChatGPT 4.1 measure of data intensity.

smaller and statistically insignificant announcement returns, suggesting that AI capability alone is insufficient to generate value without complementary data resources. Similarly, *HighAcqAI* × *HighTarAI* is economically small and statistically insignificant, indicating that pairing AI capabilities on both sides does not, by itself, enhance short-term value creation in the absence of data intensity.

On the lower end of the AI spectrum, transactions involving low-AI acquirers are associated with weak or negative market reactions. The coefficients on *LowAcqAI* × *HighTarData* are negative and insignificant, while *LowAcqAI* × *HighTarAI* is significantly negative in the shorter event windows. These results suggest that targets with strong AI or data assets do not create value when acquired by firms lacking sufficient AI capability, consistent with an inability to fully leverage those assets post-merger.

Overall, the results provide strong support for the hypothesis that value creation in AI-related M&A is driven by complementarity rather than by AI or data assets in isolation. Announcement gains accrue primarily when high-AI acquirers acquire data-intensive targets, while mismatches, where either AI capability or data intensity is lacking, are associated with muted or negative market responses.

4 Innovation Outcomes following AI-Data Mergers

Our findings show that mergers between high-AI acquirers and data-intensive targets create significant value. We next examine the source of these gains. Because innovation is a key driver of firm value (Bloom and Van Reenen, 2002; Nicholas, 2008; Pástor and Veronesi, 2009), we test whether combining AI's analytical capabilities with data-rich targets enhances post-merger innovation. Data assets are critical for innovation (Beraja, Yang, and Yuchtman, 2023), and AI's ability to uncover patterns and generate insights from large datasets (Babina et al., 2024) suggests that their integration should yield complementary innovation gains.

A key challenge is endogeneity: high-AI acquirers and data-rich targets may self-select into mergers due to pre-existing innovation strength, and post-merger innovation gains may reflect ongoing trends rather than causal effects. To address this concern, we adopt a quasi-experimental design (Bena and Li, 2014; Seru, 2014), comparing completed mergers (treatment group) to withdrawn bids (control group). Because bid withdrawal is plausibly exogenous to innovation, this approach approximates random treatment assignment of merger completion.

We identify withdrawn bids between 2009 and 2019, resulting in 112 control cases. The treatment group comprises completed mergers over the same period, matched to withdrawn bids by acquirer-target industry pair (using 4-digit SIC codes) and announcement date within a three-year window. For each withdrawn bid, we select up to ten completed deals with the closest relative-size ratios (target assets divided by acquirer assets), excluding unmatched observations. The final sample includes 58 withdrawn and 188 completed; sample construction details are provided in Internet Appendix Table IB. Patent and citation data are obtained from the Extended KPSS database (Kogan et al., 2017).

Using a three (four)-year pre- and post-announcement panel and negative binomial count model, we estimate the following differences-in-differences regression to assess the impact of AI-data integration on innovation:

$$\begin{aligned}
Patent_{ij,t} = \alpha &+ \beta_1 After_{ij,t} + \beta_2 After_{ij,t} \times Treat_{ij} \\
&+ \beta_3 After_{ij,t} \times HighAcqAI_i \\
&+ \beta_4 After_{ij,t} \times HighTarData_j \\
&+ \beta_5 After_{ij,t} \times HighAcqAI_i \times HighTarData_j \\
&+ \beta_6 After_{ij,t} \times Treat_{ij} \times HighAcqAI_i \\
&+ \beta_7 After_{ij,t} \times Treat_{ij} \times HighTarData_j \\
&+ \beta_8 After_{ij,t} \times Treat_{ij} \times HighAcqAI_i \times HighTarData_j \\
&+ \gamma\, Combined\ Company\ Characteristics_{ij,t} \\
&+ Deal\ FE + Year\ FE + \varepsilon_{ij,t}.
\end{aligned} \tag{7}$$

The dependent variable $Patent_{ij,t}$ is either combined patent applications (*Patent Application*) or combined citations (*Patent Citation*) of acquirer i and target j in year t. *Patent Application* is the total patent filings by both firms pre-merger and by the combined firm post-merger; *Patent Citation* is defined analogously using citation counts. $After_{ij,t}$ equals one for post-merger years (from *t+1* to *t+4*), and zero otherwise. $Treat_{ij}$ equals one for completed mergers (treatment group) and zero for withdrawn bids (control group).

The interaction $After_{ij,t} \times Treat_{ij}$ captures the average effect of merger completion on innovation, while higher-order interactions isolate the incremental contribution of acquirer AI capability, target data intensity, and their complementarity. $HighAcqAI_i$ and $HighTarData_j$ are indicators for the above-median AI capability and target data intensity, respectively. Their interactions capture the complementarity between AI and data. Combined firm characteristics are size-weighted averages of acquirer and target attributes. All specifications include deal and year fixed effects.

— Table 7 about here —

Table 7 provides strong causal evidence that post-merger innovation gains from M&A are driven by the complementarity between acquirer AI capability and target data intensity, rather than AI or data in isolation. Panel A uses *Patent Application* as the dependent variable, while Panel B uses *Patent Citation*, capturing both the quantity and impact of innovation. Columns (1)–(2) examine innovation outcomes over three-year pre- and post announcement windows, and columns (3)–(4) extend the analysis to four-year windows.

Across all specifications, the coefficients on $After_{ij,t} \times Treat_{ij} \times HighAcqAI_i$ and $After_{ij,t} \times Treat_{ij} \times HighTarData_j$ are negative or statistically insignificant, indicating that neither acquirer AI capability nor target data intensity alone is sufficient to generate post-merger innovation gains. In contrast, the coefficient on the quadruple interaction term, $After_{ij,t} \times Treat_{ij} \times HighAcqAI_i \times HighTarData_j$, is consistently positive and statistically significant. This results shows that completed mergers between high-AI acquirers and data-intensive targets generate substantially greater increases in both patenting activity and patent citations relative to comparable withdrawn deals.

These findings imply that innovation gains arise only when AI capability and data assets are jointly integrated through merger completion. Mergers lacking this alignment fail to produce similar benefits and may even suppress innovation, consistent with an inability to effectively exploit data resources without sufficient AI capability. Together, the results identify AI–data complementarity as a key mechanism underlying the superior value creation observed in earlier analyses of announcement returns and merger synergies.

Building on Beraja, Yang, and Yuchtman (2023), who shows that data-rich environments foster AI innovation, Table 8 examines whether the innovation gains documented earlier are specifically AI-related. Using the USPTO Artificial Intelligence Patent Dataset (AIPD) (Pairolero et al., 2025), we focus on patents explicitly classified as AI-related, including machine learning, natural language processing, computer vision, and AI hardware. To mitigate noise arising from the relative scarcity of AI patents, we restrict the sample to deals in which both the acquirer and the target held AI patents prior to the merger. We then replicate the same withdrawn-bid research design and matching procedure used in the broader innovation analyses and re-estimate Equation 7 with *AI Patent Application* as the outcome.

— Table 8 about here —

The results provide strong evidence that post-merger AI innovation is driven by AI-data complementarity. Across all specifications and both event windows, the quadruple interaction term $After_{ij,t} \times Treat_{ij} \times HighAcqAI_i \times HighTarData_j$ is positive and statistically significant.[11] This coefficient captures the incremental increase in AI-related patenting for completed mergers, relative to withdrawn bids, when a high-AI acquirer integrates a data-intensive target. The effect is economically meaningful and becomes even stronger in the longer [-4,+4] window, consistent with the idea that realizing AI innovation from newly acquired data requires time for integration, model development, and validation.

In contrast, AI capability or data intensity alone does not generate comparable gains. The coefficients on $After_{ij,t} \times Treat_{ij} \times HighAcqAI_i$ are statistically insignificant, indicating that even AI-capable acquirers do not increase AI patenting after acquisitions in the absence of data-rich targets. Similarly, $After_{ij,t} \times Treat_{ij} \times HighTarData_j$ is neg-

[11] $After_{ij,t}$ equals one for post-merger years (from *t+2* to *t+4*), and zero otherwise. The post-merger period of AI patent regression starts from *t+2* because the application of AI technologies to newly acquired data after a merger typically requires additional time for integration and adaptation. Specifically, AI patents require several additional steps, such as incorporating the acquired data into their existing infrastructure, designing and training AI models on this expanded dataset, and validating and refining these models to generate patentable outputs.

ative and statistically significant in several specifications, suggesting that acquiring data-intensive targets without sufficient AI capability may hinder AI innovation, potentially due to integration frictions or an inability to translate raw data into AI-driven technological advances.

The lower-order interactions reinforce this interpretation. While $After_{ij,t} \times HighTarData_j$ is positive, indicating that data intensity is association with stronger AI innovation trends in general, the negative $After_{ij,t} \times HighAcqAI_i \times HighTarData_j$ term shows that these trends do not translate into realized AI innovation absent merger completion. Together, these patterns highlight the importance of merger-induced integration in unlocking AI-specific innovation gains.

Overall, Table 8 demonstrates that the innovation benefits of AI-driven M&A extend beyond general patenting to AI-specific technological advances. AI-related innovation increases only when AI-capable acquirers combine their analytical expertise with data-rich targets, confirming that AI–data complementarity is not only a driver of value creation and general innovation, but also a direct mechanism for advancing frontier AI technologies after mergers.

5 Conclusion

This paper examines the influence of corporate artificial intelligence (AI) on merger and acquisition outcomes. Our findings indicate that acquirers with strong AI capabilities are more likely to seek data-AI skilled employees and data-rich target firms. Moreover, acquirers with substantial AI expertise achieve superior acquisition performance, as evidenced by higher announcement returns. Acquisitions by high-AI firms generate greater combined wealth effects without paying a higher premium, suggesting the creation of synergetic value. These acquirers could also have larger shares of synergy gains, indicating strong bargaining power generated by AI capability. Further analysis reveals that this performance is driven by the integration of AI capabilities with data assets. Using exogenous withdrawn deals as a control group, we show that acquirers with significant AI expertise who target data-rich firms experience notable post-merger increases in patent filings and citations, particularly for AI-related patent filings, thereby indicating enhanced innovation (AI Innovation) and long-term value creation.

Our findings contribute to the M&A literature by identifying a novel source of value in the AI era: the strategic complementarity between AI capabilities and data assets. More broadly, by highlighting the value generated through the interplay of AI talent and data, our study informs ongoing debates on balancing data privacy with economic efficiency.

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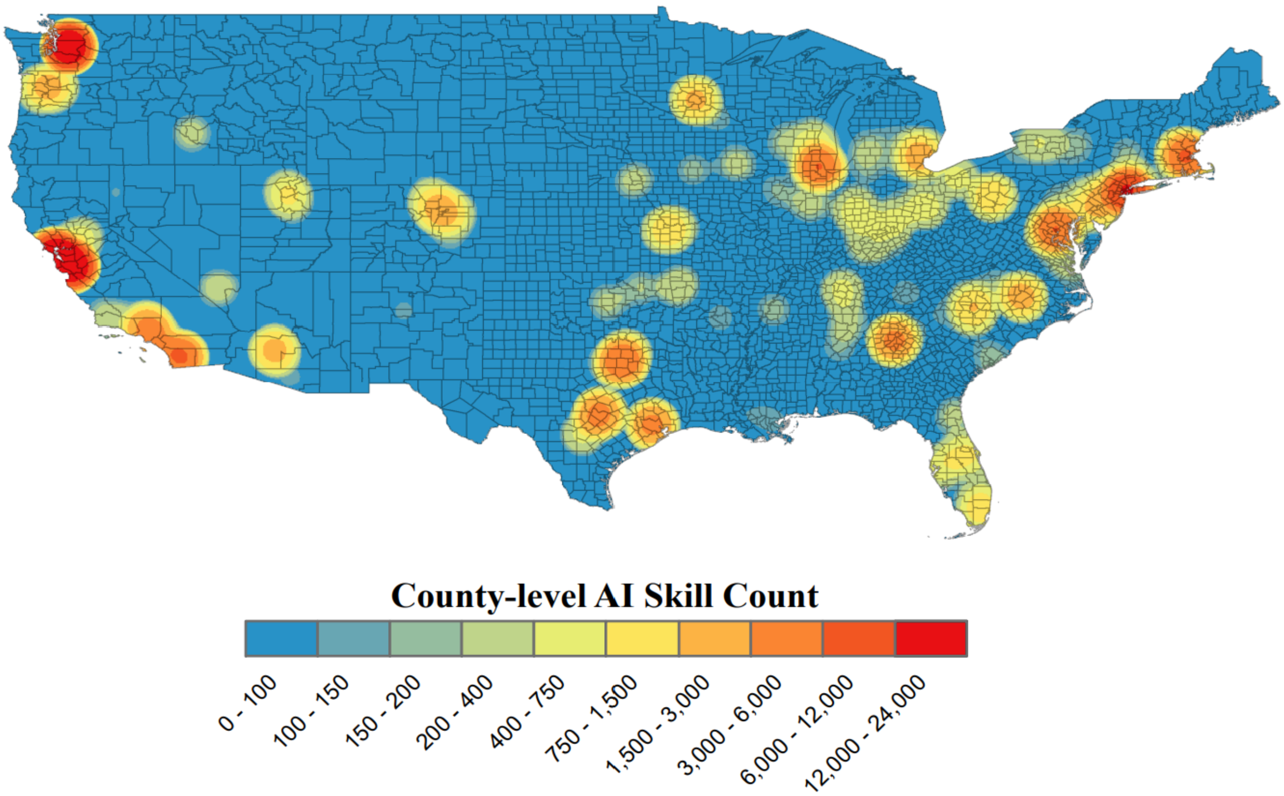

Figure 1: Geographic Distribution of AI Skills
The county-level AI skill count measures the total number of AI-related skills held by employees in our sample, aggregated at the county level. Skills are identified from LinkedIn profiles based on employees' primary reported work locations. Warmer colors on the map indicate higher concentrations of AI talent.

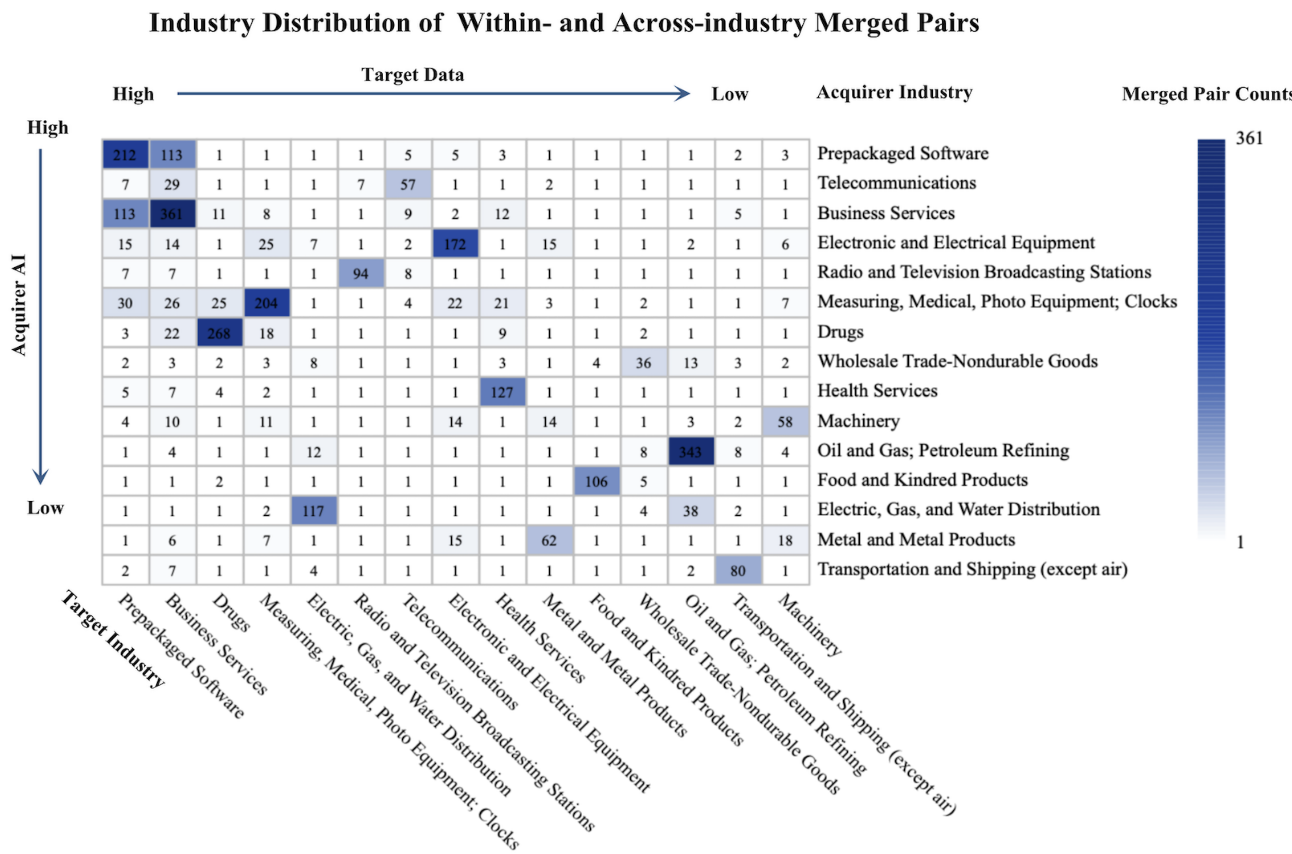

Figure 2: Industry Distribution of Within- and Across-industry Merged Pairs
This figure shows the industry distribution of all merged pairs, including both within- and cross-industry transactions. We select the 15 most frequent acquirer industries and the 15 most frequent target industries, ranking acquirers by their AI capability and targets by data intensity. The vertical axis lists acquirer industries in descending order of AI capability, while the horizontal axis displays target industries ordered by data intensity. Each cell reports the number of observed deals for a given acquirer-target industry pair, capturing merger activity across industry combinations.

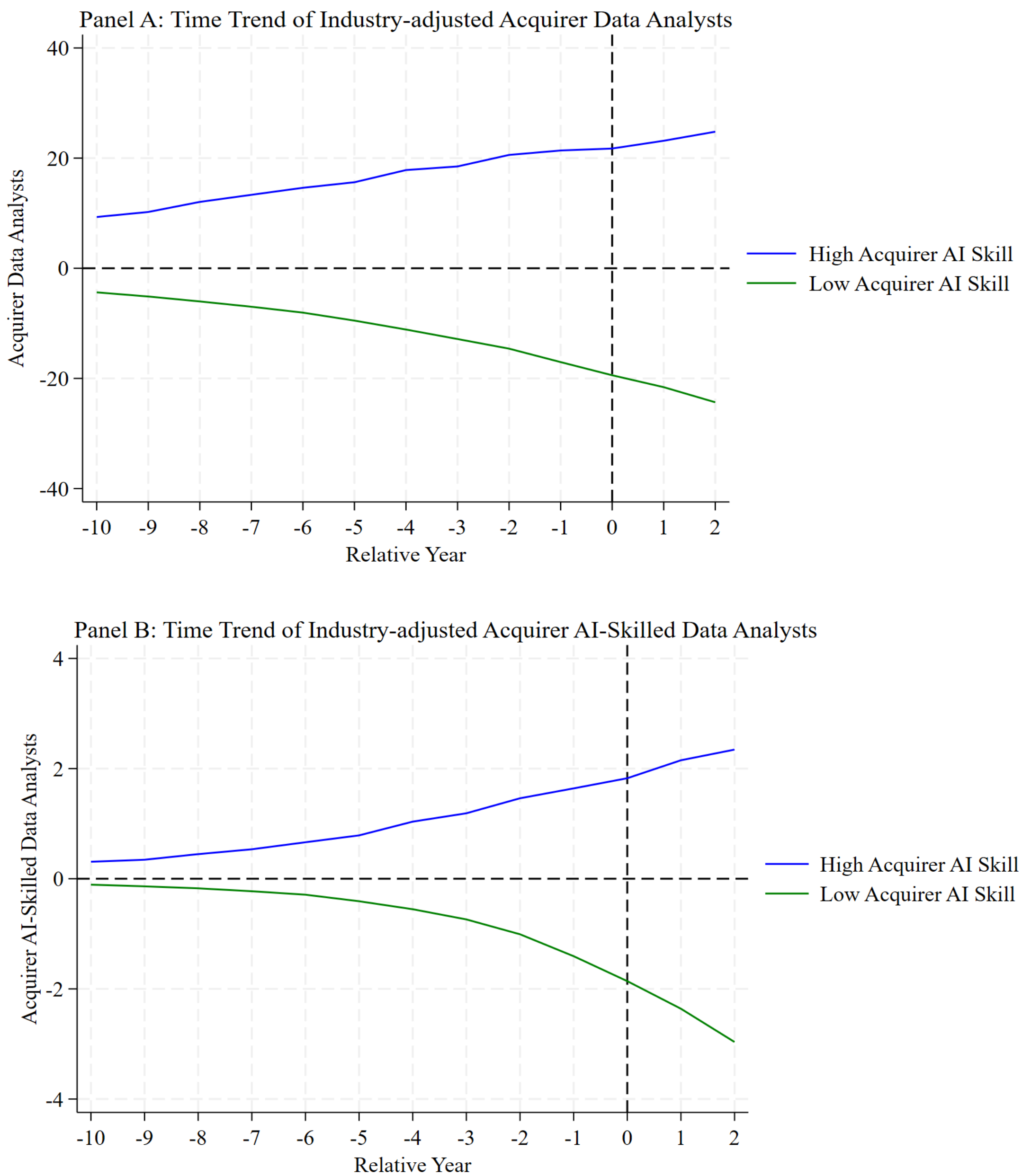

Figure 3: Time Series of Data Analytics Employees
This figure plots the industry-adjusted average number of data analysts in high-AI and low-AI acquirers from 10 years before to 2 years after the M&A announcement year. Acquirers are classified as high or low AI based on the median AI skill level derived from LinkedIn data in the year preceding the transaction. Data analysts are identified job titles containing the keyword "data." The blue line represents high-AI acquirers, and the the green line represents low-AI acquirers; both series are industry-adjusted. Panel A shows trends for all data analysts, while Panel B focuses on data analysts who also report AI-related skills in their LinkedIn profiles.

Table 1:
Summary Statistics

This table reports descriptive statistics for M&A transactions from 2009 to 2019. Panels A–D present the mean, median, standard deviation, minimum, and maximum for acquirer, target, deal, and combined firm characteristics, respectively. Panel E summarizes employee- and experience-related variables based on matched SDC-LinkedIn data. The sample is drawn from the Thomson One Platinum SDC M&A database and includes filtered deals with public acquirers worldwide and U.S. public or private targets announced between January 1, 2009, and December 31, 2019. Appendix A provides detailed variable definitions.

	(1) N	(2) Mean	(3) SD	(4) Min	(5) Max
Panel A: Acquirer Characteristics:					
Acq_Emp	4,464	1,456.49	4,348.27	1.00	80,220.67
Acq_AIEmp	4,464	23.02	148.47	0.00	4,576.92
Acq_AISkill	4,464	31.55	222.37	0.00	7,412.58
LnAcqAIEmp	4,464	1.28	1.49	0.00	7.39
LnAcqAISkill	4,464	1.38	1.59	0.00	7.73
LnAcqEmp	4,464	5.37	2.28	0.00	10.72
Leverage	4,464	0.26	0.22	0.00	0.92
Intanratio	4,464	0.28	0.23	0.00	0.83
RD	4,464	0.03	0.06	0.00	0.29
ROA	4,464	0.02	0.14	-0.68	0.24
Size	4,464	7.24	1.91	2.69	12.76
Tobin's Q	4,464	2.00	1.18	0.75	7.91
Panel B: Target Characteristics:					
Tar_Emp	4,464	291.03	1,744.01	0.00	84,096.83
Tar_AIEmp	4,464	3.63	25.94	0.00	793.75
Tar_AISkill	4,464	4.83	36.78	0.00	1,213.08
LnTarAISkill	4,464	0.48	0.96	0.00	4.54
TargetStatus	4,464	0.16	0.36	0.00	1.00
DataIntensity	996	384.67	2635.15	0.00	24016.00
DataIntensity_GPT	991	1.48	0.81	0.00	3.00
HighTarData	996	0.33	0.47	0.00	1.00
HighTarData_GPT	991	0.40	0.49	0.00	1.00
Panel C: Deal Characteristics:					
AllStock	4,464	0.04	0.20	0.00	1.00
Challenge	4,464	0.01	0.12	0.00	1.00

Table 1 Continued

	(1) N	(2) Mean	(3) SD	(4) Min	(5) Max
Conglomerate	4,464	0.39	0.49	0.00	1.00
Crossbor	4,464	0.05	0.21	0.00	1.00
Hightechdeal	4,464	0.21	0.41	0.00	1.00
Rel_DealVal	4,464	0.25	0.42	0.01	2.65
CAR[-3,+3]	4,464	0.01	0.08	-0.21	0.25
CAR[-4,+4]	4,464	0.01	0.09	-0.23	0.26
CAR[-5,+5]	4,464	0.01	0.09	-0.25	0.29
TarCAR[-2,+2]	1,046	0.14	0.19	-0.28	1.22
TarCAR[-3,+3]	1,046	0.14	0.20	-0.40	1.34
CombinedCAR	586	0.03	0.09	-0.24	0.27
Premium	586	0.04	0.05	-0.13	0.20
Acquirer's Share of Synergy Gains	586	-0.00	0.06	-0.19	0.14
Panel D: Combined Firm Characteristics:					
AI Patent Application	1,094	35.17	92.02	0.00	534
Patent Application	1,768	101.85	298.72	0.00	2054
Patent Citation	1,768	404.99	1242.06	0.00	8033
Panel E: Employee/Experience Characteristics:					
AI skills owned	8,521,432	0.03	0.25	0.00	16.00
Duration of Acq. Experience (month)	9,750,774	57.68	69.02	1.00	613.00
Duration of Tar. Experience (month)	4,310,924	56.75	69.22	1.00	613.00

Table 2:
Likelihood of Acquirer-Target Firm Pairing

This table reports coefficient estimates from conditional logit models using observed acquirer-target pairs and a matched control sample of potential deals. The dependent variable equals one for the observed acquirer-target pairs and zero for control pairs. Columns (1) to (3) report results for three different control samples. Variable definitions are provided in Appendix A. All specifications include acquirer and target characteristics (size, Tobin's Q, leverage, ROA, sales growth, and R&D intensity), indicators for diversifying and same-state deals, and deal fixed effects. Robust z-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) Ind-Size	(2) Ind-Size-ROA	(3) Ind-Size-ROA-Q
HighAcqAI*HighTarData	0.613**	0.717**	0.671**
	(2.09)	(2.38)	(2.24)
HighAcqAI	-1.747***	-1.859***	-1.648***
	(-6.59)	(-6.73)	(-6.00)
HighTarData	-0.190	-0.162	-0.147
	(-1.07)	(-0.80)	(-0.71)
Acquirer, Target Controls	Yes	Yes	Yes
Diversifying, Same State	Yes	Yes	Yes
Deal FE	Yes	Yes	Yes
No. of Observations	4,396	4,159	4,045
No. of Actual Deals	531	514	507
No. of Control Deals	3,865	3,645	3,538
Pseudo R^2	0.405	0.361	0.359

Table 3:
Acquirer AI Capabilities and Acquisition Announcement Returns

This table reports results from announcement return regressions. The dependent variables are cumulative abnormal returns (CARs) over the [-3, +3], [-4,+4], and [-5,+5] windows, estimated using the market model with parameters derived from the CRSP value-weighted index over [-240, -11] trading days estimation window. Columns (1)-(3) examine the effect of acquirer AI skill intensity on CARs, while Columns (4)-(6) examine the effect of the number of AI-skilled employees. All specifications include acquirer industry and state $\times$ year 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) CAR[-3,+3]	(2) CAR[-4,+4]	(3) CAR[-5,+5]	(4) CAR[-3,+3]	(5) CAR[-4,+4]	(6) CAR[-5,+5]
LnAcqAISkill	0.005***	0.006***	0.006***			
	(2.77)	(2.92)	(2.73)			
LnAcqAIEmp				0.005**	0.005***	0.005**
				(2.58)	(2.70)	(2.53)
LnAcqEmp	-0.003***	-0.003***	-0.003**	-0.003**	-0.003**	-0.003**
	(-2.68)	(-2.65)	(-2.42)	(-2.52)	(-2.47)	(-2.26)
Size	-0.008***	-0.008***	-0.008***	-0.008***	-0.008***	-0.008***
	(-6.61)	(-6.07)	(-6.03)	(-6.54)	(-6.00)	(-5.97)
Tobin's Q	-0.003	-0.003	-0.003	-0.003	-0.003	-0.003
	(-1.47)	(-1.42)	(-1.33)	(-1.45)	(-1.40)	(-1.32)
Leverage	0.026***	0.021**	0.019*	0.026***	0.021**	0.019*
	(2.97)	(2.23)	(1.79)	(2.96)	(2.23)	(1.79)
ROA	0.008	0.003	0.013	0.008	0.003	0.013
	(0.51)	(0.15)	(0.73)	(0.51)	(0.15)	(0.72)
Intanratio	0.002	0.002	-0.002	0.002	0.002	-0.002
	(0.27)	(0.26)	(-0.22)	(0.26)	(0.25)	(-0.23)

Table 3 Continued

	(1) CAR[-3,+3]	(2) CAR[-4,+4]	(3) CAR[-5,+5]	(4) CAR[-3,+3]	(5) CAR[-4,+4]	(6) CAR[-5,+5]
RD	-0.084**	-0.080*	-0.062	-0.083**	-0.079*	-0.061
	(-2.01)	(-1.75)	(-1.29)	(-1.99)	(-1.73)	(-1.27)
TargetStatus	-0.016***	-0.015***	-0.017***	-0.016***	-0.015***	-0.017***
	(-3.35)	(-2.95)	(-3.12)	(-3.35)	(-2.95)	(-3.12)
AllStock	-0.015*	-0.009	-0.012	-0.015*	-0.009	-0.012
	(-1.73)	(-0.99)	(-1.21)	(-1.72)	(-0.98)	(-1.21)
Conglomerate	-0.002	-0.005	-0.007*	-0.002	-0.005	-0.007*
	(-0.72)	(-1.29)	(-1.95)	(-0.72)	(-1.28)	(-1.95)
Rel_DealVal	0.018***	0.015***	0.018***	0.018***	0.015***	0.018***
	(3.40)	(2.85)	(3.02)	(3.39)	(2.84)	(3.02)
Hightechdeal	-0.002	-0.004	-0.007	-0.001	-0.004	-0.007
	(-0.28)	(-0.66)	(-1.09)	(-0.27)	(-0.65)	(-1.09)
Challenge	0.010	0.002	0.002	0.010	0.003	0.002
	(0.94)	(0.21)	(0.17)	(0.95)	(0.22)	(0.18)
Crossbor	-0.011	0.003	0.016	-0.011	0.003	0.016
	(-0.58)	(0.15)	(0.67)	(-0.58)	(0.16)	(0.67)
Observations	4,325	4,325	4,325	4,325	4,325	4,325
R^2	0.217	0.210	0.211	0.217	0.210	0.211
Acq. ind. FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Acq. State × Year FE	Yes	Yes	Yes	Yes	Yes	Yes

Table 4:
Acquirer AI Capabilities and Acquisition Announcement Returns: IV Estimates

This table reports the result from a 2SLS approach adopting an instrumental variable. Columns (1) reports the first stage regression, where *LnAcqAISkill* is regressed on the instrument that measures acquirer firm-level exposure to the local supply of AI talents. Columns (2)-(4) report the second stage results. All the Columns include all the baseline control variables. Standard errors are clustered at the 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[-3,+3]	(3) CAR[-4,+4]	(4) CAR[-5,+5]
IV	12.832*** (4.12)			
LnAcqAISkill		0.029* (1.72)	0.031* (1.68)	0.040** (2.00)
LnAcqEmp	0.460*** (30.21)	-0.014* (-1.78)	-0.014* (-1.70)	-0.019** (-2.04)
Size	0.179*** (9.59)	-0.012*** (-3.53)	-0.012*** (-3.35)	-0.015*** (-3.59)
Tobin's Q	0.024 (1.00)	-0.003 (-1.40)	-0.002 (-0.93)	-0.002 (-0.91)
Leverage	0.025 (0.20)	0.029*** (2.80)	0.022** (2.00)	0.021* (1.72)
ROA	-0.349* (-1.93)	0.042** (2.16)	0.039* (1.75)	0.055** (2.28)
Intanratio	-0.300** (-2.20)	0.018 (1.56)	0.021* (1.75)	0.020 (1.46)
RD	2.222*** (4.19)	-0.110* (-1.79)	-0.118* (-1.76)	-0.131* (-1.78)
TargetStatus	0.017 (0.37)	-0.017*** (-3.52)	-0.017*** (-3.28)	-0.018*** (-3.23)
AllStock	0.126 (1.57)	-0.017* (-1.81)	-0.009 (-0.86)	-0.018 (-1.56)

Table 4 Continued

	(1) LnAcqAISkill	(2) CAR[-3,+3]	(3) CAR[-4,+4]	(4) CAR[-5,+5]
Conglomerate	0.031	-0.005	-0.006*	-0.009**
	(0.85)	(-1.27)	(-1.66)	(-2.24)
Rel_DealVal	-0.051	0.024***	0.023***	0.025***
	(-1.15)	(3.81)	(3.46)	(3.38)
Hightechdeal	0.133*	-0.010	-0.014**	-0.016**
	(1.85)	(-1.61)	(-2.10)	(-2.23)
Challenge	0.024	0.008	0.003	0.001
	(0.22)	(0.70)	(0.20)	(0.05)
Crossbor	0.340*	-0.020	-0.010	-0.005
	(1.87)	(-1.02)	(-0.44)	(-0.20)
Observations	3,961	3,961	3,961	3,961
F Statistic	34.69	34.69	34.69	34.69
Acq. ind. FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Acq. State. × Year FE	Yes	Yes	Yes	Yes

Table 5:
Evaluation of Combined Wealth Effects and Acquisition Premium

This table reports regressions of *CombinedCAR*, *Premium*, and the bidder's share of combined synergy gains for deals involving public targets. In Column (1), the dependent variable is *CombinedCAR*, defined as the weighted average of the target's CAR [-41, +3] and the acquirer's CAR [-3, +3], using market capitalizations measured on day -42 for the target and day -4 for the acquirer as weights. Column (2) uses *Premium*, calculated as the target's CAR [-41, +3] multiplied by its market capitalization on day -42, and scaled by the combined market capitalizations of the target (day -42) and the acquirer (day -4). Column (3) examines the *Acquirer's Share of Synergy Gains*,defined as *CombinedCAR* minus *Premium*. Column (4) and (5) report regressions of target CARs. All specifications include acquirer industry fixed effects, year fixed effects and acquirer state × year fixed effects. Robust t-statistics clustered at the firm-level are reported in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

	(1) Combined CAR	(2) Premium	(3) Acquirer's Share of Synergy Gains	(4) Target CAR [-2,+2]	(5) Target CAR [-3,+3]
LnAcqAISkill	0.018**	0.004	0.013*	0.045**	0.048***
	(2.20)	(1.00)	(1.96)	(2.48)	(2.67)
LnAcqEmp	-0.012**	-0.003	-0.007*	-0.022*	-0.026**
	(-2.22)	(-1.22)	(-1.76)	(-1.70)	(-2.12)
Size	-0.006	0.001	-0.008*	-0.033**	-0.029**
	(-1.14)	(0.21)	(-1.79)	(-2.50)	(-2.12)
Tobin's Q	-0.011	-0.006	-0.004	0.035**	0.033*
	(-1.44)	(-1.43)	(-0.59)	(2.18)	(1.75)
Leverage	0.020	0.013	0.007	-0.143	-0.142
	(0.39)	(0.48)	(0.17)	(-1.57)	(-1.57)
ROA	0.070	0.027	0.040	0.179	0.132
	(1.07)	(0.73)	(0.78)	(1.10)	(0.80)
Intanratio	-0.022	-0.004	-0.019	-0.023	-0.030
	(-0.52)	(-0.19)	(-0.66)	(-0.31)	(-0.39)

Table 5 Continued

	(1) Combined CAR	(2) Premium	(3) Acquirer's Share of Synergy Gains	(4) Target CAR [-2,+2]	(5) Target CAR [-3,+3]
RD	-0.133	-0.043	-0.132	-0.208	-0.131
	(-0.81)	(-0.48)	(-1.03)	(-0.65)	(-0.39)
AllStock	0.000	-0.013	0.012	-0.110***	-0.107***
	(0.02)	(-1.09)	(0.88)	(-3.07)	(-3.10)
Conglomerate	-0.004	-0.007	0.004	0.028	0.012
	(-0.29)	(-0.99)	(0.37)	(0.86)	(0.36)
Rel_DealVal	0.022*	0.026***	-0.003	-0.091***	-0.095***
	(1.81)	(3.26)	(-0.33)	(-3.37)	(-3.69)
Hightechdeal	-0.006	0.001	-0.002	0.054	0.049
	(-0.23)	(0.05)	(-0.11)	(0.76)	(0.66)
Challenge	0.039*	0.024*	0.014	-0.007	0.006
	(1.83)	(1.76)	(0.91)	(-0.14)	(0.11)
Crossbor	0.055	0.063	-0.015	-0.369***	-0.267**
	(0.76)	(1.24)	(-0.31)	(-2.86)	(-2.27)
Observations	363	363	363	363	363
R^2	0.539	0.563	0.520	0.606	0.599
Acq. ind. FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
Acq. State × Year FE	Yes	Yes	Yes	Yes	Yes

Table 6:
Testing the Synergy between Acquirer AI and Target Data

This table reports the effects of different acquirer-target combinations on acquirer announcement returns. Deals are classified into eight groups based on the acquirer's AI capability, the target's AI capability, and the target's data intensity. Due to collinearity among these indicators, three groups are omitted as reference categories, and the table reports results for the remaining five groups. All specifications include acquirer industry fixed effects, year fixed effects,acquirer industry $\times$ year fixed effects and acquirer state $\times$ 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) CAR[-3,+3]	(2) CAR[-4,+4]	(3) CAR[-5,+5]
HighAcqAI $\times$ HighTarData	0.061**	0.062**	0.065**
	(2.18)	(2.08)	(2.12)
HighAcqAI $\times$ LowTarData	0.030	0.036	0.040
	(1.32)	(1.51)	(1.63)
HighAcqAI $\times$ HighTarAI	0.000	-0.005	-0.013
	(0.00)	(-0.27)	(-0.64)
LowAcqAI $\times$ HighTarData	-0.020	-0.029	-0.031
	(-0.65)	(-0.99)	(-1.05)
LowAcqAI $\times$ HighTarAI	-0.054**	-0.051*	-0.038
	(-2.24)	(-1.93)	(-1.40)
LnAcqEmp	-0.013***	-0.013**	-0.011**
	(-2.77)	(-2.60)	(-2.27)
Size	0.002	0.002	0.001
	(0.27)	(0.34)	(0.17)
Tobin's Q	-0.012	-0.006	-0.009
	(-1.31)	(-0.56)	(-0.76)
Leverage	-0.075	-0.082	-0.081
	(-1.51)	(-1.48)	(-1.34)
ROA	-0.062	-0.051	-0.015
	(-1.13)	(-0.74)	(-0.19)
Intanratio	-0.024	-0.017	-0.034
	(-0.55)	(-0.40)	(-0.71)

Table 6 Continued

	(1) CAR[-3,+3]	(2) CAR[-4,+4]	(3) CAR[-5,+5]
RD	-0.239	-0.225	-0.234
	(-1.51)	(-1.33)	(-1.24)
AllStock	0.011	0.014	0.008
	(0.44)	(0.51)	(0.28)
Conglomerate	-0.027	-0.029	-0.032
	(-1.54)	(-1.53)	(-1.56)
Rel_DealVal	-0.003	-0.002	-0.003
	(-0.23)	(-0.14)	(-0.19)
Hightechdeal	-0.029	-0.032	-0.039
	(-1.04)	(-1.02)	(-1.22)
Challenge	0.015	-0.001	-0.011
	(0.61)	(-0.05)	(-0.42)
Crossbor	0.109	0.205***	0.007
	(1.55)	(3.09)	(0.11)
Observations	429	429	429
R^2	0.628	0.639	0.629
Acq. ind. FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Acq. ind. × Year FE	Yes	Yes	Yes
Acq. State × Year FE	Yes	Yes	Yes

Table 7:
Post-Merger Innovation Performance

This table reports estimates of the treatment effect of mergers on post-merger innovation output. Panel A presents negative binomial regression results using a panel data set that includes completed deals (treatment group) and withdrawn bids (control group), estimated over (-3,+3) and (-4,+4) year windows centered on the deal announcement year. The dependent variable is the annual sum of the acquirer's and the target's innovation output measured by patent applications. Panel B reports analogous results using patent citation to measure innovation. Definitions of all the variables are provided in Appendix A. All specifications include deal and year fixed effects. z-statistics are reported in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Panel A: Post-merger Patent Applications

	Patent Application			
	(1)	(2)	(3)	(4)
	[-3,+3]	[-3,+3]	[-4,+4]	[-4,+4]
After×Treat×HighAcqAI×HighTarData	1.593***	1.392***	1.266***	1.151***
	(3.89)	(3.24)	(3.32)	(2.86)
After×Treat×HighAcqAI	-0.369	-0.200	-0.191	-0.065
	(-1.22)	(-0.64)	(-0.69)	(-0.22)
After×Treat×HighTarData	-1.357***	-1.136***	-1.257***	-1.094***
	(-4.28)	(-3.35)	(-4.24)	(-3.43)
After×Treat	0.578**	0.444*	0.559***	0.455**
	(2.51)	(1.85)	(2.66)	(2.06)
After×HighAcqAI×HighTarData	-1.698***	-1.447***	-1.415***	-1.213***
	(-4.57)	(-3.74)	(-4.09)	(-3.35)
After×HighAcqAI	0.717***	0.577**	0.677***	0.525**
	(2.59)	(2.05)	(2.65)	(2.02)
After×HighTarData	1.439***	1.157***	1.373***	1.110***
	(5.01)	(3.82)	(5.13)	(3.90)
After	-0.843***	-0.727***	-0.960***	-0.824***
	(-3.89)	(-3.27)	(-4.88)	(-4.05)
Weighted_Size		0.002		0.028
		(0.04)		(0.92)
Weighted_Q		0.016		0.027
		(0.45)		(0.92)
Weighted_Leverage		-0.376*		-0.380**
		(-1.73)		(-2.02)

Table 7 Continued

	Patent Application			
	(1)	(2)	(3)	(4)
	[-3,+3]	[-3,+3]	[-4,+4]	[-4,+4]
Weighted_Intanratio		-0.484**		-0.690***
		(-2.08)		(-3.64)
Weighted_ROA		0.095		-0.015
		(0.38)		(-0.07)
Observations	1,045	1,007	1,329	1,257
Deal and Year FE	Yes	Yes	Yes	Yes

Panel B: Post-merger Patent Citations

	Patent Citation			
	(1)	(2)	(3)	(4)
	[-3,+3]	[-3,+3]	[-4,+4]	[-4,+4]
After×Treat×HighAcqAI×HighTarData	1.557***	1.282**	1.329**	1.241**
	(2.61)	(2.15)	(2.43)	(2.28)
After×Treat×HighAcqAI	-0.592	-0.319	-0.466	-0.226
	(-1.34)	(-0.71)	(-1.16)	(-0.56)
After×Treat×HighTarData	-1.643***	-1.197**	-1.511***	-1.213***
	(-3.34)	(-2.46)	(-3.36)	(-2.71)
After×Treat	1.015***	0.684*	0.963***	0.644*
	(2.80)	(1.87)	(2.94)	(1.95)
After×HighAcqAI×HighTarData	-2.184***	-2.020***	-1.984***	-1.951***
	(-4.01)	(-3.71)	(-3.98)	(-3.91)
After×HighAcqAI	1.329***	1.082***	1.283***	0.984***
	(3.26)	(2.61)	(3.46)	(2.62)
After×HighTarData	1.847***	1.496***	1.725***	1.487***
	(4.08)	(3.34)	(4.17)	(3.61)
After	-1.918***	-1.600***	-1.922***	-1.561***
	(-5.63)	(-4.66)	(-6.22)	(-5.02)

Table 7 Continued

	Patent Citation			
	(1)	(2)	(3)	(4)
	[-3,+3]	[-3,+3]	[-4,+4]	[-4,+4]
Weighted_Size		0.199***		0.210***
		(5.69)		(7.05)
Weighted_Q		0.051		0.068**
		(1.34)		(2.08)
Weighted_Leverage		-1.346***		-1.352***
		(-4.43)		(-5.13)
Weighted_Intanratio		-0.799***		-0.990***
		(-2.95)		(-4.40)
Weighted_ROA		0.168		0.028
		(0.46)		(0.09)
Observations	1,004	967	1,268	1,198
Deal and Year FE	Yes	Yes	Yes	Yes

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

This table reports estimates of the treatment effect of mergers on post-merger AI-related innovation. It presents negative binomial regression results using a panel data set that includes completed deals (treatment group) and withdrawn bids (control group), estimated over (-3,+3) and (-4,+4) year windows centered on the deal announcement year. The dependent variable is the annual sum of the acquirer's and the target's AI-related patent applications. Definitions of all variables are provided in Appendix A. All specifications include deal and year fixed effects. z-statistics are reported in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

	AI Patent Application			
	(1)	(2)	(3)	(4)
	[-3,+3]	[-3,+3]	[-4,+4]	[-4,+4]
After×Treat×HighAcqAI×HighTarData	1.150**	1.173**	1.416***	1.333***
	(2.35)	(2.55)	(3.09)	(3.14)
After×Treat×HighAcqAI	-0.156	0.197	-0.296	0.129
	(-0.42)	(0.53)	(-0.84)	(0.38)
After×Treat×HighTarData	-0.405	-0.287	-0.831**	-0.601*
	(-1.10)	(-0.87)	(-2.33)	(-1.86)
After×Treat	-0.263	-0.516**	0.010	-0.311
	(-0.95)	(-1.97)	(0.04)	(-1.23)
After×HighAcqAI×HighTarData	-1.355***	-1.264***	-1.422***	-1.210***
	(-3.21)	(-3.13)	(-3.56)	(-3.21)
After×HighAcqAI	0.421	0.065	0.630**	0.168
	(1.28)	(0.20)	(2.01)	(0.55)
After×HighTarData	0.727**	0.533*	0.959***	0.639**
	(2.31)	(1.90)	(3.10)	(2.28)
After	0.121	0.354	-0.190	0.153
	(0.48)	(1.48)	(-0.76)	(0.65)
Weighted_Size		0.244***		0.221***
		(4.86)		(5.16)
Weighted_Q		0.140**		0.179***
		(2.38)		(3.78)

Table 8 Continued

	AI Patent Application			
	(1)	(2)	(3)	(4)
	[-3,+3]	[-3,+3]	[-4,+4]	[-4,+4]
Weighted_Leverage		-1.023***		-0.950***
		(-3.78)		(-4.00)
Weighted_Intanratio		-1.247***		-1.456***
		(-4.48)		(-6.39)
Weighted_ROA		-0.118		-0.186
		(-0.30)		(-0.56)
Observations	790	759	1,012	956
Deal and Year FE	Yes	Yes	Yes	Yes

Appendix A Variable definitions and data sources

Acq_AIEmp Average monthly number of AI-skilled employees at the acquirer firm over the 12 months preceding the deal announcement.

Acq_AISkill Average monthly number of AI-related skills at the acquirer firm over the 12 months preceding the deal announcement.

Acq_Emp Average monthly number of employees at the acquiring firm over the 12 months preceding the deal announcement.

LnAcqAIEmp Natural logarithm of one plus Acq_AIEmp.

LnAcqEmp Natural logarithm of one plus Acq_Emp.

LnAcqAISkill Natural logarithm of one plus $Acq\_AISkill$.

HighAcqAI Indicator variable equal to one if the acquirer's $Acq\_AISkill$ is above the sample median, and zero otherwise.

Intanratio Ratio of intangible assets to total assets for the acquirer as of the fiscal year-end preceding the deal announcement, computed as `intan/at` using Compustat data.

Leverage Acquirer leverage as of the fiscal year-end preceding the deal announcement, computed as `(dlc+dltt)/at` using Compustat data.

ROA Return on assets of acquirer as of the fiscal year-end preceding the deal announcement, computed as `ni/at` using Compustat data.

RD R&D expense of the acquirer as of the fiscal year-end preceding the deal announcement, computed as `xrd/at` and set to zero if missing, using Compustat data.

Salesgrowth Annual sales growth of the acquirer as of the fiscal year-end preceding the deal announcement, using Compustat data.

Size Natural logarithm of acquirer size, measured as market capitalization 11 days prior to the deal announcement for deal-level regressions, and the natural log of book assets as of the fiscal year-end preceding the deal announcement for firm-level regressions. Market capitalization is computed as `abs(prc*shrout)/1000`, and book assets equal `at`, using Compustat and CRSP data.

Tobin's Q Tobin's Q of the acquirer as of the fiscal year-end preceding the deal announcement, computed as `(at-ceq+prcc_f*csho)/at` using Compustat data.

DataIntensity Frequency of data security–related keywords in Item 1A risk disclosures from firms' 10-K filings.

DataIntensity_GPT Alternative measure of data intensity generated using a large language model applied to firms' 10-K filings.

HighTarData Indicator variable equal to one if the target's *DataIntensity* is above the sample median, and zero otherwise.

HighTarData_GPT Indicator variable equal to one if the target's *DataIntensity_GPT* is above the sample median, and zero otherwise.

Tar_AIEmp Average monthly number of AI-skilled employees at the target firm over the 12 months preceding the deal announcement.

Tar_AISkill Average monthly number of AI-related skills at the target firm over the 12 months preceding the deal announcement.

Tar_Emp Average monthly number of employees at the target firm over the 12 months preceding the deal announcement.

Tar_Intanratio Ratio of intangible assets to total assets for the target as of the fiscal year-end preceding the deal announcement, computed as `intan/at` using Compustat data.

Tar_Leverage Target leverage as of the fiscal year-end preceding the deal announcement, computed as `(dlc+dltt)/at` using Compustat data.

Tar_RD R&D intensity of the target as of the fiscal year-end preceding the deal announcement, computed as `xrd/at` and set to zero if missing, using Compustat data.

Tar_ROA Return on assets of the target as of the fiscal year-end preceding the deal announcement, computed as `ni/at` using Compustat data.

Tar_Salesgrowth Annual sales growth rate of the target as of the fiscal year-end preceding the deal announcement, using Compustat data.

Tar_Size Natural logarithm of target book assets (`at`) as of the fiscal year-end preceding the deal announcement, using Compustat data.

Tar_Tobin's Q Tobin's Q of the target as of the fiscal year-end preceding the deal announcement, computed as `(at-ceq+prcc_f*csho)/at` using Compustat data.

TargetStatus Indicator variable equal to one if the target is public according to SDC, and zero otherwise.

CAR[-3,+3] Market-model cumulative abnormal returns (CARs) over the $[-3, +3]$ event window surrounding the M&A announcement. Market-model parameters are estimated using the CRSP value-weighted index over $[-240, -11]$ trading days relative to the announcement date.

CAR[-4,+4] Market-model cumulative abnormal returns (CARs) over the $[-4, +4]$ event window, estimated using the CRSP value-weighted index over $[-240, -11]$ trading days.

CAR[-5,+5] Market-model cumulative abnormal returns (CARs) over the $[-5,+5]$ event window, estimated using the CRSP value-weighted index over $[-240,-11]$ trading days.

CombinedCAR Weighted average of the target's CAR $[-41,+3]$ and the acquirer's CAR $[-3,+3]$, using market capitalizations on day -42 (target) and day -4 (acquirer) as weights. The target's CAR $[-41,+3]$ is estimated using a market model fitted over $[-240,-42]$.

Premium Acquisition premium, calculated as the target's CAR $[-41,+3]$ multiplied by its market capitalization on day -42, scaled by the combined market capitalizations of the target (day -42) and the acquirer (day -4).

AllStock Indicator variable equal to one if the transaction is paid entirely in stock (SDC variable `ofstock` = 100), and zero otherwise.

Conglomerate Indicator variable equal to one if the acquirer and target operate in different industries—defined as different 4-digit SIC codes in Table 2 and different 2-digit SIC codes elsewhere–and zero otherwise.

Challenge Indicator variable equal to one if the SDC variable `cha` equals "Yes," and zero otherwise.

Crossbor Indicator variable equal to one if the acquirer and target are from different countries, and zero otherwise, based on SDC data.

HighTechdeal Indicator variable equal to one if both the acquirer's and target's 4-digit SIC codes fall within a predefined set of high-technology industries,[12] and zero otherwise.

Rel_DealVal Deal value divided by the acquirer's total assets, using deal value data from SDC and total assets from Compustat.

SameState Indicator variable equal to one if the acquirer and target are located in the same U.S. state, and zero otherwise.

AI Patent Application Total number of AI-related patent applications filed by the acquirer and the target. A patent is classified as AI-related if `predict93_any_ai` equals one in the AIPD.

Patent Application Total number of patent applications filed by the acquirer and the target.

Patent Citation Total number of forward citations received by patents filed by the acquirer and the target.

[12] 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, or 7379.

Weighted_Intanratio Asset-weighted average of acquirer and target intangible asset ratios prior to the acquisition, and the intangible asset ratio of the combined firm after the acquisition.

Weighted_Leverage Asset-weighted average of acquirer and target leverage prior to the acquisition, and leverage of the combined firm after the acquisition.

Weighted_ROA Asset-weighted average of acquirer and target ROA prior to the acquisition, and ROA of the combined firm after the acquisition.

Weighted_Size Asset-weighted average of acquirer and target size prior to the acquisition, and size of the combined firm after the acquisition.

Weighted_Q Asset-weighted average of acquirer and target Tobin's Q prior to the acquisition, and Tobin's Q of the combined firm after the acquisition.

Internet Appendix: When AI Acquires Data: Strategic Complementarities in M&A

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January 1, 2026

IA GPT Measure: Testing the Synergy between Acquirer AI and Target Data

This table provides a robustness check of Table 6 by replacing the target data measure with a GPT-generated measure. The sample was classified into eight groups according to the acquirer's AI level, the target's AI level, and the target's data level. Because of overlaps among these classifications, three groups were automatically omitted, and the final table presents results for the remaining five groups. All specifications control for acquirer industry fixed effects, year fixed effects,acquirer industry × year fixed effects and acquirer state × 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) CAR[-3,+3]	(2) CAR[-4,+4]	(3) CAR[-5,+5]
HighAcqAI × HighTarData	0.071**	0.087***	0.093***
	(2.31)	(2.80)	(3.04)
HighAcqAI × LowTarData	0.032	0.038	0.043*
	(1.25)	(1.49)	(1.67)
HighAcqAI × HighTarAI	0.004	0.000	-0.007
	(0.22)	(0.00)	(-0.37)
LowAcqAI × HighTarData	0.012	0.018	0.019
	(0.44)	(0.65)	(0.68)
LowAcqAI × HighTarAI	-0.047*	-0.042	-0.031
	(-1.79)	(-1.53)	(-1.07)
LnAcqEmp	-0.011**	-0.010**	-0.009*
	(-2.47)	(-2.23)	(-1.88)
Size	-0.000	-0.000	-0.001
	(-0.01)	(-0.03)	(-0.27)
Tobin's Q	-0.013	-0.007	-0.009
	(-1.34)	(-0.68)	(-0.79)
Leverage	-0.078	-0.076	-0.068
	(-1.40)	(-1.26)	(-1.05)
ROA	-0.046	-0.034	0.004
	(-0.81)	(-0.48)	(0.05)
Intanratio	0.012	0.028	0.010
	(0.26)	(0.60)	(0.21)

Appendix Table IA Continued

	(1) CAR[-3,+3]	(2) CAR[-4,+4]	(3) CAR[-5,+5]
RD	-0.201	-0.183	-0.188
	(-1.24)	(-1.03)	(-0.96)
AllStock	0.008	0.012	0.004
	(0.31)	(0.41)	(0.14)
Conglomerate	-0.032*	-0.034*	-0.036*
	(-1.77)	(-1.73)	(-1.76)
Rel_DealVal	-0.004	-0.004	-0.005
	(-0.31)	(-0.26)	(-0.31)
Hightechdeal	-0.033	-0.037	-0.044
	(-1.21)	(-1.24)	(-1.46)
Challenge	0.010	-0.006	-0.016
	(0.39)	(-0.22)	(-0.58)
Crossbor	-0.291	-0.233	-0.343*
	(-1.44)	(-1.06)	(-1.96)
Observations	428	428	428
R^2	0.609	0.614	0.619
Acq. ind. FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Acq. ind. × Year FE	Yes	Yes	Yes
Acq. State × Year FE	Yes	Yes	Yes

IB Post-Merger Innovation Treatment Sample Criteria

Criteria	Treated Deals Left	Control Deals Left
Acquirer-target industry pairs that match those of the withdrawn bids in the control sample	335	68
Announcement year falls within a three-year window centered around the announcement year of the control bids to minimize time-related differences	258	58
For each control bid, select up to 10 matched completed deal with the closest relative-size ratio (target assets divided by acquirer assets)	188	58

IC Post-Merger AI Innovation Treatment Sample Criteria

Criteria	Treated Deals Left	Control Deals Left
Innovative acquirers and target firms	778	40
Acquirer-target industry pairs that match those of the withdrawn bids in the control sample	192	40
Announcement year falls within a three-year window centered around the announcement year of the control bids to minimize time-related differences	142	34
For each control bid, select up to 10 matched completed deal with the closest relative-size ratio (target assets divided by acquirer assets)	115	34