Artificial Intelligence Capital and Complementary Acquisitions

Abstract

This paper studies whether firms' accumulation of artificial intelligence (AI) capital shapes their participation in the market for corporate control. We combine AI-skilled employment data with a capitalization model to estimate the implied price and accumulated quantity of installed AI capital. A one-standard-deviation increase in AI capital is associated with a 2.21-percentage-point increase in the acquisition probability. The relation remains significant after controlling for AI-skilled employment, data-skilled hiring, organizational capital, and patent capital, whereas AI-skilled employment alone does not exhibit the same predictive relation. Cross-sectionally, the AI–acquisition relation is stronger among large firms. AI capital also predicts firms' subsequent demand for AI-skilled labor beyond existing AI employment and prior AI hiring activity. Consistent with complementarity between installed AI capabilities and additional AI expertise, AI-rich acquirers disproportionately select targets that employ AI-skilled workers, both in realized public-to-public deals and relative to matched potential targets. We further find that the positive relation between AI capital and acquisition activity is weaker when firms face higher financing costs, consistent with financing conditions affecting firms' ability to act on acquisition opportunities. The main relation is also present in instrumental-variable estimates using firms' pre-2010 exposure to AI-intensive universities. Together, the findings show that accumulated AI capabilities are associated with both greater acquisitiveness and the acquisition of complementary AI human capital, with implications for firm boundaries and the persistence of incumbent advantage.

Keywords: Artificial intelligence capital; Mergers; Acquisitions
JEL Classification Codes: D22, L11, G34, O33

1. Introduction

The rapid diffusion of artificial intelligence (AI) is reshaping how firms produce, innovate, and compete. Existing evidence shows that firms investing in AI subsequently experience greater sales, employment, market value, and product innovation (Babina et al., 2024). Much less is known, however, about whether AI changes firm boundaries by affecting participation in the market for corporate control. This omission is important because acquisitions allow firms to redeploy existing capabilities across a broader asset base and obtain technologies and human capital more rapidly than through internal development (Hoberg and Phillips, 2025). Progress on this question has been limited partly because existing measures primarily capture AI investment or adoption rather than the accumulated productive capability created by those investments. We address this limitation by developing firm-year measures of AI capital that recover its implied quantity and shadow price. Using these measures, we examine how AI capital is associated with firms' acquisition activity and whether accumulated AI capabilities systematically shape the types of targets with which firms match.

Major technological shifts reshape firm boundaries, trigger resource reallocation, and induce creative destruction (Aghion and Howitt, 1992). AI represents such a technological transformation. AI can alter production processes, investment opportunities, and competitive advantages across a broad range of industries (Agrawal et al., 2019; Goldfarb et al., 2023). A longstanding literature argues that firms respond to economic, technological, and regulatory shocks through mergers because acquisitions provide a rapid means of reallocating assets and adapting to new competitive environments (Faria, 2008; Gort, 1969; Harford, 2005; Mitchell and Mulherin, 1996). These arguments suggest that firms with greater AI capital should be better positioned to identify and exploit opportunities arising from the AI transformation. They may also use acquisitions to deploy their existing AI capabilities across additional assets or obtain the complementary resources needed to extend those capabilities. We therefore expect AI capital to increase a firm's likelihood of becoming a bidder.

The acquisition response to AI capital should not be uniform across firms. Developing AI-related infrastructure, recruiting specialized employees, reorganizing production, and integrating AI into decision processes entail substantial fixed costs and complementary organizational invest-

ment (Brynjolfsson et al., 2021). These features generate economies of scale that favor large firms. Consistent with this view, digital capital is concentrated among large incumbents, and the growth associated with AI investment increases with firm size (Babina et al., 2024; Tambe et al., 2020). Large incumbents may also rely more heavily on acquisitions because they face fewer opportunities to grow rapidly through internal capital expenditure and R&D alone and possess the managerial and financial capacity required to search for and integrate targets (Akcigit and Kerr, 2018; Hoberg and Phillips, 2025; Phillips and Zhdanov, 2013). We therefore expect the positive relation between AI capital and acquisition activity to be concentrated among large incumbent firms.

Our analysis requires distinguishing AI investment from AI capital. Following the stock-based approach of Tambe et al. (2020), we define AI capital as the accumulated stock of firm-specific productive capabilities created through AI investment and embodied in algorithms, specialized human capital, and the organizational routines that integrate AI into production and decision-making. This construct differs from both AI employment and AI adoption. Employee-based measures capture an important investment input but not prior accumulation or the extent to which employee knowledge has been embedded in code, teams, and routines (Babina et al., 2024). Adoption measures identify whether a firm uses AI but not the scale, quality, or organizational integration of that use (McElheran et al., 2025). Because the productivity of technologies depends on accumulated complementary investments (Brynjolfsson et al., 2021; Teece, 1986), neither measure alone captures the resulting capital stock. Like other intangible capital, AI capital provides productive services over multiple periods and depreciates through technological obsolescence and employee turnover (Eisfeldt and Papanikolaou, 2013; Hall, 2001; Peters and Taylor, 2017).

Measuring AI capital is difficult because most internally generated AI-related assets do not appear separately on balance sheets, and economically similar investments may have different values across firms. We address this challenge by combining employment data and a dynamic capital-accumulation model. Babina et al. (2024) use employee résumés and job postings to identify firm-level AI investment. Building on their approach, we use AI-skilled employment as an observable root that links AI investment to firm value. Importantly, we do not equate AI employees with AI capital. Employee expertise creates firm-level capital only to the extent that it becomes embedded in code,

models, teams, workflows, and organizational routines.

Our measurement procedure applies the established capital-accumulation framework of Hall (2001), following its firm-level digital-capital implementation in Tambe et al. (2020). The procedure proceeds in two steps. First, for each year, we estimate the market value associated with AI-skilled employment. Second, we apply the capital-accumulation framework to separate this value into the implied quantity of AI capital, K, and its shadow price, Q. K captures the model-implied accumulated stock of AI-related productive capabilities, whereas Q captures differences in the price of installed AI capital across firms and over time. This decomposition allows two firms with similar observable AI employment to have different quantities and prices of AI capital, reflecting differences in their histories of accumulation and the value of the capabilities they have developed. Our primary measure is K, while AI employment and Q provide complementary measures. We conduct several validation tests. First, AI employment and K increase markedly during the 2010s and are concentrated in industries in which AI use is expected to be intensive, particularly business equipment and telecommunications. Second, K is strongly associated with AI employment and is positively associated with independently constructed measures of organizational and patent capital. The incremental association between K and data- or IT-related job postings is insignificant. Among the intangible-capital proxies, organizational capital has the strongest association with K, consistent with organizational processes being an important component of firms' ability to deploy AI. Third, we find that K predicts firms' subsequent demand for AI-skilled labor. The relation remains significant after controlling for existing AI employment, prior AI hiring demand, and broader IT- and data-related hiring demand.

We document two main findings. First, firms with greater AI capital are more likely to become bidders. A one-standard-deviation increase in K is associated with a 2.21-percentage-point increase in the annual probability of becoming a bidder, representing 9.34% of the unconditional acquisition rate of 23.66%. We also document cross-sectional heterogeneity by firm size. The AI–acquisition relation is stronger among large firms when comparing the top and bottom quartiles of the size distribution. However, the interaction between AI capital and firm size becomes statistically insignificant once firm fixed effects are included. We therefore interpret the size results as evidence of persistent cross-

sectional heterogeneity rather than as evidence that the acquisition response to AI capital increases as an individual firm grows. Second, AI capital is systematically related to the types of targets that firms acquire. In realized public-to-public acquisitions, bidders with greater AI capital acquire targets with greater AI-skilled employment. More importantly, matched potential-pair tests show that this pattern reflects differential target selection. Conditional on the realized acquirer and a set of comparable potential targets, targets employing AI-skilled workers become relatively more likely to be selected as acquirer AI capital rises. On the extensive margin, a one-standard-deviation increase in acquirer AI capital increases the differential probability of selecting a target with AI-skilled employees by approximately 5.4 to 8.1 percentage points across the alternative matching procedures. These results are consistent with complementarity in acquisition matching between bidders' installed AI capabilities and targets' AI human capital.

To strengthen identification, we instrument AI capital using $AIExposure_{2010}$, which captures a firm's historical connection to universities with strong AI programs. This predetermined exposure predicts firms' subsequent ability to accumulate AI capital but predates the acceleration of commercial AI investment around 2012. The coefficient on instrumented AI capital remains significant. Thus, the positive AI-capital–acquisition relation is also present when variation in AI capital is instrumented using firms' pre-2010 exposure to AI-intensive universities.

The evidence is consistent with a complementary capability-building interpretation and with financing conditions affecting firms' ability to execute acquisitions. The first set of results concerns complementary capability-building acquisitions. Existing knowledge increases a firm's ability to recognize, absorb, and apply related external knowledge (Chen et al., 2023; Cohen and Levinthal, 1990; Hammer et al., 2022; Teece, 1986). AI capital and AI-skilled labor should therefore be complementary rather than substitutes. Acquisitions allow firms to obtain employees together with their code, routines, and working relationships. In realized public-to-public acquisitions, bidders with greater AI capital acquire targets with greater AI-skilled employment. More importantly, matched potential-pair tests show that this pattern reflects differential target selection: conditional on the realized acquirer and a set of comparable potential targets, AI-intensive targets become relatively more likely to be selected as acquirer AI capital rises. Together, these results indicate complementarity in acqui-

sition matching between bidders' installed AI capabilities and targets' AI human capital. The second set of results concerns financing conditions. The positive relation between AI capital and acquisition activity is weaker when firms face higher costs of equity or debt. These results are consistent with favorable financing conditions facilitating firms' ability to act on acquisition opportunities.

We conduct additional tests to assess competing explanations. We find no affirmative evidence consistent with defensive or positioning motives, equity misvaluation, or managerial agency problems. The AI–acquisition relation does not exhibit the industry-composition heterogeneity predicted by defensive or positioning motives. AI capital is also not significantly associated with stock payment, offer premiums, bidder or target announcement returns, or bidders' long-run post-deal returns. These null results do not rule out the competing explanations, but they provide no affirmative evidence that the baseline relation is primarily driven by these mechanisms.

The paper makes three main contributions. First, we contribute to the measurement of firm-level AI investment and intangible capital. Existing studies primarily measure whether firms adopt AI or the contemporaneous flow of AI investment (Acemoglu et al., 2022; Babina et al., 2024). These measures are informative about current activity but do not distinguish the accumulation of AI capabilities from the price assigned to those capabilities. We apply the established framework for measuring intangible and digital capital (Hall, 2001; Tambe et al., 2020) to AI-related investment. Treating AI-related capabilities as a durable intangible capital stock that accumulates and depreciates over time, we construct separate firm-year estimates of the model-implied quantity and shadow price of AI capital. Our contribution is therefore not a new capital-accumulation model, but its application to AI investment and the construction and validation of firm-level measures of accumulated AI capabilities. The resulting quantity measure also has predictive content beyond contemporaneous AI employment: AI capital forecasts firms' subsequent demand for AI-skilled labor after controlling for existing AI employment, prior AI hiring activity, and broader technical hiring demand.

Second, we contribute to the literature on technological change, firm growth, and the market for corporate control. Prior research shows that economic and technological shocks generate merger waves and reshape firm boundaries (Gort, 1969; Harford, 2005; Mitchell and Mulherin, 1996), while recent evidence links AI investment to sales growth and product innovation (Babina et al., 2024). We

connect this literature by showing that AI capital is also associated with inorganic growth through acquisitions. The evidence further identifies economic patterns consistent with this relation. AI capital is associated with target selection toward firms employing AI-skilled workers, and its relation with acquisition activity is weaker when financing costs are higher. These results show that AI is systematically associated with the organizational boundaries through which firms expand and reallocate capabilities.

Third, we contribute to the literature on persistent firm heterogeneity and superstar firms (Autor et al., 2020; Corhay et al., 2025; Firooz et al., 2025). Prior research shows that large firms adopt new technologies more intensively and derive greater benefits from AI (Babina et al., 2024; Tambe et al., 2020). We show that AI capital is concentrated among large firms and that its association with acquisition activity is stronger among larger incumbents in the cross-section. Moreover, AI-rich bidders disproportionately select AI-intensive targets from matched alternatives and tend to acquire targets that are small relative to their own size. These findings suggest that acquisitions may provide a scalable way for large incumbents to extend installed AI capabilities beyond their existing organizational boundaries, with potential implications for the persistence of incumbent advantage.

The remainder of the paper proceeds as follows. Section 2 develops the conceptual framework and empirical predictions. Section 3 describes the data. Section 4 develops and validates the firm-level AI-capital measures. Section 5 presents the baseline evidence linking AI capital to acquisition activity. Section 6 addresses identification. Section 7 examines mechanisms. Section 8 presents deal-level results. Section 9 reports additional analyses and robustness tests. Section 10 concludes.

2. Conceptual Framework and Empirical Predictions

2.1. The Big-Data Revolution and Acquisition Activity

Major technological transformations reshape firm boundaries by changing production technologies, competitive conditions, and resource allocation across firms. Creative destruction predicts that resources flow toward firms better positioned to exploit new technologies, while firms that fail to adapt lose competitive ground or exit the market (Aghion and Howitt, 1992). Technological transformations therefore create both incentives and opportunities for firms to reconfigure their asset bases.

The big-data revolution represents such a transformation in shaping production, investment, innovation, and firm growth, with potentially economy-wide consequences (Abis and Veldkamp, 2024; Babina et al., 2024; Goldfarb and Tucker, 2019; Kogan et al., 2017). AI is a central component of this transformation and is increasingly viewed as a general-purpose technology in altering business processes and market structure (Acemoglu et al., 2022; Babina, 2026; Barrios et al., 2024). As firms differ in their ability to accumulate and deploy AI-related resources, the big-data revolution generates persistent heterogeneity in their capacity to exploit and respond to technological change. AI capital is therefore both an outcome of this transformation and a strategic resource.

A longstanding literature links merger waves to economic and technological shocks. Acquisitions allow firms to rapidly obtain productive assets, technologies, customers, and organizational capabilities. Gort (1969) argues that shocks change firms' assessments of asset values and create opportunities to reallocate assets through mergers. Subsequent studies similarly link takeover activity to economic and technological shocks (Faria, 2008; Mitchell and Mulherin, 1996). Harford (2005) shows that merger waves arise when such shocks coincide with sufficient capital liquidity, enabling firms to act on reallocation opportunities. More recent evidence also indicates that acquisitions remain an important channel through which incumbent firms respond to technological and regulatory change (Charoenwong et al., 2024; Hoberg and Phillips, 2025; Phillips and Zhdanov, 2013).

Therefore, firms with greater AI capital should have both stronger incentives and greater ability to participate in the market for corporate control as acquirers during the big-data revolution.

Prediction 1 (Acquisitiveness). *Firms with greater AI capital are more likely to become bidders.*

2.2. AI Capital and Firm Size

The acquisition response to AI capital should not be uniform across firms. The fixed costs of developing AI-related infrastructure, recruiting specialized employees, reorganizing production, and integrating AI into decision processes create scale economies in AI adoption. Consistent with this view, larger firms adopt new technologies more intensively and derive greater benefits (Brynjolfsson et al., 2023; Tambe et al., 2020). AI investment and its associated growth effects are likewise concentrated among larger firms (Babina et al., 2024). These complementarities allow large firms to

accumulate more AI capital and deploy it across a broader set of activities.

The same forces also imply heterogeneous acquisition responses. Large firms possess fewer profitable opportunities for rapid organic expansion through internal investment, making acquisitions a relatively more attractive growth strategy (Akcigit and Kerr, 2018; Phillips and Zhdanov, 2013).

AI capital should therefore generate stronger acquisition responses among large firms.

Prediction 2 (Size heterogeneity). *The positive relation between AI capital and acquisition activity is stronger among large incumbents.*

2.3. Acquisition of AI Human Capital

Existing capabilities are particularly important for knowledge-intensive technologies because they determine a firm's ability to recognize, assimilate, and commercially apply external knowledge (Cohen and Levinthal, 1990). In the context of AI, firm-level AI capital and AI-skilled labor are complementary inputs. AI employees contribute specialized knowledge and judgment, while a firm's existing computing infrastructure, organizational routines, and related human capital enable that expertise to be deployed effectively. An established AI capability may therefore increase, rather than diminish, the marginal value of additional AI human capital. This complementarity has implications for both internal and external capability accumulation. Firms with greater installed AI capital should continue to demand additional AI-skilled labor as they expand and deepen their use of AI. They may obtain such expertise through external hiring or, when relevant knowledge is embedded in firms and teams, through acquisitions.

External hiring may nevertheless be slow or costly when specialized skills are scarce or when relevant knowledge is embedded in established teams. M&A provides an alternative means of acquiring employees together with their tacit knowledge, organizational routines, and working relationships (Bai et al., 2026). Consistent with this view, Chen et al. (2024) show that firms respond to shortages of high-skilled workers by acquiring relatively small companies that employ the required talent. The acquired workers tend to possess skills and occupations similar to those of the bidder's existing workforce, suggesting that acquirers seek human capital that complements and extends established

capabilities. More generally, mergers are more likely between firms with related technological knowledge bases (Bena and Li, 2014) and frequently match firms with similar characteristics (Huang and Xie, 2023; Rhodes-Kropf and Robinson, 2008).

This mechanism is particularly relevant to AI because AI knowledge is embodied to a substantial extent in specialized employees and teams. Gofman and Jin (2024) show that the departure of AI professors reduces AI startup formation and financing among their students, highlighting the importance and limited substitutability of AI human capital. Similarly, digital incumbents tend to acquire targets in technological areas in which they already operate (Ederer et al., 2025). An AI-rich bidder should therefore be better able to identify, integrate, and scale the expertise embedded in an AI-intensive target, generating a larger ownership-specific surplus from the acquisition. Accordingly, we expect complementarity in acquisition matching: firms with greater AI capital should be more likely to acquire targets that employ AI-skilled workers.

Prediction 3 (Acquisition of AI Human Capital). *Firms with greater AI capital are more likely to acquire targets employing AI-skilled workers.*

2.4. Financing and the Execution of Acquisitions

Acquisition activity depends not only on firms' incentives to expand but also on their ability to finance and execute transactions. Favorable financing conditions can facilitate firms' ability to respond to technological shocks through acquisitions (Almeida et al., 2011; Harford, 2005; Huang et al., 2024). We therefore examine whether the AI–acquisition relation is weaker under higher financing costs.

Prediction 4 (Financing conditions). *The AI–acquisition relation is stronger under lower financing costs.*

2.5. Competing Explanations

Several alternative explanations could nevertheless generate a positive relation between AI capital and acquisition activity. These explanations generate predictions that differ from our framework.

First, Gorton et al. (2009) develop **defensive** and **positioning** motives for acquisitions. Under the defensive motive, an "eat or be eaten" dynamic arises during periods of industry restructuring.

Managers acquire other firms to increase firm size and thereby reduce the probability of subsequently being acquired. This motive predicts that acquisitions will be concentrated in industries with numerous small and medium-sized potential targets and will produce relatively poor shareholder outcomes. Under the positioning motive, firms undertake acquisitions to become more attractive targets. This motive predicts greater acquisition activity in industries containing large potential acquirers and more favorable shareholder outcomes because such acquisitions create an option for subsequent resale.

Second, the observed relation may reflect **misvaluation** rather than technological reallocation. Under the misvaluation hypothesis, firms use overvalued equity to finance acquisitions (Harford, 2005). This explanation predicts a greater reliance on stock payments than predicted by technological-shock theories.

Third, improved financing capacity could enable managers to pursue acquisitions for private benefits rather than maximize shareholder value. Under this agency explanation, AI-rich acquirers may pursue value-destroying deals.

The empirical tests provide evidence relevant to these explanations by examining industry composition, acquisition announcement returns, and methods of payment.

3. Data and sample

3.1. AI Employment and Job Postings

Firm-level measures of employment and hiring are from Babina et al. (2024), who construct them using separate résumé and job-posting databases. The two sources capture distinct but complementary dimensions of firms' specialized human capital: the stock of workers already employed by the firm and the firm's demand for additional labor.

AI-related jobs are identified based on the AI-relatedness of workers' underlying skills rather than relying solely on job titles or industry classifications, and are further aggregated to the firm-year level (Babina et al., 2024). We use AI-skilled employment as the observable labor input underlying our AI-capital construction and *ShareAI* as only a complementary measure of the firm's existing AI-skilled employment. The AI-employment and AI-capital measures span 2009–2018. Lagged AI-capital

measures are then used to predict acquisition outcomes through 2019.

Job postings provide a complementary measure of firms' demand for skilled labor. Using the corresponding firm-year measures, we define $ShareAIPost$, $ShareITPost$, and $ShareDataPost$ as the shares of a firm's job postings associated with AI-, IT-, and data-related skills, respectively. These posting-based measures are particularly useful for our predictive-validation tests because they capture hiring demand separately from the existing employee stock used in constructing AI capital.

3.2. Compustat sample

The AI-employment and job-posting measures are merged with Compustat and CRSP. The primary firm-year sample comprises U.S. public firms with non-missing lagged AI-employment information from 2010 to 2019. Following Edmans et al. (2012), we exclude firms in the financial (SIC 6000–6999) and utility (SIC 4000–4949) industries. We obtain accounting information from Compustat and stock-price data from the Center for Research in Security Prices (CRSP).[1] The resulting dataset contains 15,671 firm-year observations with non-missing lagged AI capital, before requiring non-missing firm-level controls. Table **1** presents summary statistics for the main variables.

3.3. Merger and acquisition sample

We obtain acquisition data from the Securities Data Corporation (SDC) Mergers and Acquisitions database. The initial sample consists of deals announced between January 1, 2010 and December 31, 2019 in which the bidder is publicly traded and has available CRSP and Compustat data. We require the bidder to own less than 50% of the target six months before the announcement and to seek ownership of more than 50% following the transaction. Targets may be public firms, private firms, or subsidiaries. We exclude deals classified as restructuring, liquidation, bankruptcy, reverse takeovers, leveraged buyouts, going private transactions, government-owned involvement, spin-offs, recapitalizations, repurchases, exchange offers, and divestitures. We also exclude bidders and targets in the financial (SIC 6000–6999) and utility (SIC 4000–4949) industries.

[1] We adhere to the commonly accepted practice of maintaining a minimum six-month gap between fiscal-year-end accounting data and CRSP market data to ensure that financial-report information is publicly available (see, e.g., Alford et al., 1994; Fama and French, 1992).

Table **A2** presents the annual distribution of the 2,178-deal analysis sample with non-missing deal-level and firm-level controls. SDC provides information on the target's public status as public, private, or subsidiary when the classification is available, as well as whether the offer is diversified, a tender offer, or friendly. SDC also reports details on the payment method (full cash or full stock), relative deal size, number of bidders, and toehold positions. For analyses requiring target-side AI measures, we restrict the sample to completed public-to-public acquisitions for which both the acquirer and target can be linked to Compustat/CRSP and have the required AI measures. Section *7.1* further constructs matched potential acquirer and target sets from this public-firm universe. The cumulative abnormal return (CAR) for bidders and targets is computed using a standard event study window [-1, +1], with the announcement date as day zero. Abnormal returns are measured using the market-adjusted return approach (Fuller et al., 2002). See Appendix Table **A1** for complete variable definitions.

3.4. Summary statistics

Table **1** presents summary statistics, including means, standard deviations, and selected percentiles for the variables used in the analysis. All continuous variables are winsorized at the 1% and 99% levels. Panel A reports results for the Compustat sample. The mean MnA (the annual probability of being a bidder) is 23.66% with a standard deviation of 42.50%. The mean K (the model-implied quantity of AI capital) is $557.96 million, and the mean Q (the model-implied shadow price of AI capital) is 1.06. Panel B reports results for the SDC mergers and acquisitions sample. The mean bidder CAR is 0.92%, and the mean target CAR_T is 29.18%.

4. Measuring Firm-Year AI Capital

4.1. What Is AI Capital

AI is commonly characterized as a technology that lowers the cost of prediction and changes how firms combine machine-generated predictions with human judgment (Agrawal et al., 2019). Access to an AI technology, however, does not by itself constitute a productive firm-level capability. To deploy AI, firms must hire and train specialized employees, develop or adapt algorithms and application

software, redesign workflows, and establish procedures for evaluating and acting on AI-generated outputs (Brynjolfsson et al., 2021; McElheran et al., 2025).

We define a firm's AI capital as the accumulated stock of productive capabilities created by developing and deploying AI. This stock is jointly embodied in AI-related algorithms and application software, specialized employees and teams, and the organizational knowledge and routines through which the firm integrates AI into its operations and decisions. These components are complementary. Algorithms have limited value without employees capable of developing, adapting, and evaluating them, while AI-skilled employees are more productive when supported by established technical systems and organizational processes. AI capital is therefore broader than AI human capital but narrower than the entire collection of resources used in an AI application.

The role of employees in this definition requires clarification. Firms do not fully own their employees. Nevertheless, AI-related hiring can create firm-level capital when employee expertise becomes embedded in teams, code, models, workflows, and organizational routines. This treatment parallels organizational capital, which is firm-specific and partly embodied in labor but not wholly owned by shareholders (Eisfeldt and Papanikolaou, 2013). Consistent with this interpretation, Babina et al. (2024) use employee résumés and job postings to measure firm-level AI investment and show that such investment predicts subsequent growth in sales, employment, market value, and product innovation. AI-skilled employment therefore provides an observable measure of firms' investment in building AI capabilities, but it is not equivalent to the resulting capital stock.

4.2. Why Treat AI Capabilities as Capital?

Why should this productive capability be treated as capital? AI-related expenditures use current resources but can generate productive services over multiple periods. The resulting capability also has three defining properties of capital. First, it accumulates as successive investments add to a firm's stock of technical knowledge, software, specialized expertise, and organizational routines. Second, it is durable but depreciates as models and skills become obsolete, employees leave, or organizational processes lose their relevance. Third, it is firm-specific because the same AI technology can have different productive values depending on how it is integrated into a firm's existing operations. The

finance literature similarly recognizes that expenditures on R&D, organizational capabilities, and other intangibles create capital stocks that affect firm value and investment despite being largely absent from balance sheets (Eisfeldt and Papanikolaou, 2013; Hall, 2001; Peters and Taylor, 2017).

The capital interpretation is particularly relevant to AI because AI has the characteristics of a general-purpose technology. Machine learning has diffused across industries and tasks and has generated complementary demand for research and technical skills (Goldfarb et al., 2023). Technologies typically require substantial firm-specific investment before producing measurable benefits (Teece, 1986). Brynjolfsson et al. (2021) show that complementary intangible investments can initially appear as costs and only later generate measured productivity gains. Thus, the economic value of AI does not reside only in an algorithm or an externally available AI tool, but also reflects the firm-specific capital accumulated as the firm embeds that technology into its organizational decisions.

The distinction between AI investment and AI capital motivates our empirical measures. AI-skilled employment captures the observable scale of a firm's AI-related investment. It does not, however, distinguish between a recently initiated investment and a capability accumulated over many years, nor does it capture differences in the economic value of similar investments across firms. We therefore use it as the economic root for identifying the firm value associated with AI investment rather than treating it as a complete measure of AI capital. Following Hall (2001), we view the value of installed capital as the product of its shadow price and quantity. We adapt this framework, together with the digital-capital application of Tambe et al. (2020), to separate the value associated with AI capital into its implied price, Q, and quantity, K. Q captures variation in the shadow price of installed AI capital across firms and over time, whereas K captures the corresponding accumulated quantity. This decomposition allows us to study AI as a heterogeneous capital stock rather than merely as an adoption decision or a contemporaneous labor input.[2]

4.3. Capital Accumulation Model of AI Capital

We apply an established capital-accumulation and quantity-revelation framework to measure firm-level AI capital. Hall (2001) shows that, under the model's standard assumptions, the price and

[2] AI-skilled employment may understate AI investment when firms outsource AI-related tasks (Barrios et al., 2024; Tambe et al., 2020).

quantity of installed capital can be recovered from its market value. Tambe et al. (2020) subsequently apply this framework to firm-level digital investment and use labor-based inputs to estimate the price and quantity of digital capital. We follow this established framework rather than introduce a new structural model. Our contribution is to apply the framework to AI-related investment, using AI-skilled employment as the observable economic root, and to evaluate whether the resulting firm-year measures capture economically meaningful variation in accumulated AI capabilities.

Conceptually, we treat AI capital as a form of accumulated intangible capital that grows through investment and depreciates over time. This interpretation allows the existing capital-accumulation framework to be applied to AI in the same manner that prior work applies it to other forms of intangible and digital capital.

The capital-accumulation framework is characterized by two equations, for each firm i:

$$V_t/K_t = Q_t \tag{1}$$

$$Q_t = 1 + c'(\frac{I_t}{K_{t-1}}) = 1 + \alpha \left[\frac{K_t - (1-\delta)K_{t-1}}{K_{t-1}}\right] \tag{2}$$

Equation 1 defines average Q as the ratio of the market value attributed to AI capital (V) to the model-implied stock of AI capital (K). Equation 2 defines marginal Q as one plus the marginal adjustment cost as a function of AI capital growth, measured by the current year's investment (I_t), relative to the previous year's capital (K_{t-1}). The constant 1 captures the numeraire purchase price of a unit of capital. The adjustment-cost function is assumed to be convex ($c'(x) = \alpha x$), where $\alpha > 0$ is a constant. Investment is defined as $I_t = K_t - (1-\delta)K_{t-1}$, that is, the annual increase in the capital stock net of depreciation. δ denotes the depreciation rate, and $(1-\delta)K_{t-1}$ represents the portion of the previous year's AI capital that carries forward into the current year after depreciation. Under the zero-rent economy assumptions, average and marginal Q coincide and Equation 1 equals Equation 2 (Hall, 2001; Hayashi, 1982; Tambe et al., 2020). This equality implies a unique solution for K and Q in the interval $[\min\{(1-\delta)K_{t-1}, V_t\}, \max\{(1-\delta)K_{t-1}, V_t\}]$. Assuming values for α, δ, and the initial K_{t-1}, we need only V_t to solve the equation.[3]

[3]See the derivation of this equality in Section IA.1 and the proof of the unique root in Section IA.2. Figure IA1 examines the sensitivity of the model-implied K and Q measures to alternative parameter values; the time-series path of K is substantially more stable than that of Q. The resulting K and Q measures are model-implied objects under the

Following Tambe et al. (2020), we estimate a hedonic regression to recover V_t for each year t:

$$V_{it}^{T} = \beta_{0,t} + \beta_{1,t} Root_{it} + \beta_{2,t} PPENT_{it} + \beta_{3,t} OtherAssets_{it} + \omega_j + u_{it}. \tag{3}$$

where the dependent variable V_{it}^{T} denotes the firm's total market capitalization. $PPENT_{it}$ is property, plant, and equipment, and $OtherAssets_{it}$ is other physical assets. ω_j denotes industry fixed effects, and each regression uses a rolling two-year window, $[t-1, t]$ with year and industry effects.[4] This step does not assume that financial markets perfectly price the underlying assets (Hall, 2001; Tambe et al., 2020). Instead, it allows market mispricing but only assumes that stock markets recognize AI capital as economically valuable. A testable implication is that the market recognizes the existence of AI capital; that is, $\widehat{\beta}_{1,t}$ should be positive. The estimation yields a time series of the AI-capital-related coefficient $\widehat{\beta}_{1,t}$ and a firm-year panel of predicted AI-capital values, $\widehat{V_{it}} = \widehat{\beta}_{1,t} \times Root_{it}$.

4.4. Estimation of AI Capital

Given this capital-accumulation framework, we must choose a *Root* that links firms' market value to AI capital. As Tambe et al. (2020) use labor as the economic input for capital, AI-related labor is a natural analogue for AI capital. We therefore use the AI-skilled employees at each firm as the *Root* to identify the market value of AI capital and to infer the implied price (Q) and quantity (K). Here, Q is the shadow price of AI capital, and K is the quantity of AI capital. Importantly, labor itself is not our measure of AI capital. Instead, AI-skilled employment serves as an observable root that allows the model to attribute a portion of firm value to AI capital and subsequently infer the underlying stock of AI capital.

The procedure is as follows. First, we estimate the yearly regressions in Equation 3 and obtain a firm-year panel of predicted $\widehat{V_{it}}$ for AI capital, $\widehat{V_{it}} = \widehat{\beta}_{1,t} \times Root_{it}$. Second, we accumulate AI capital each year by solving the equality between the average-Q and marginal-Q conditions, using assumed values for α, δ, and $K_{i,t-1}$ at $t = 0$. Following Tambe et al. (2020), we initialize the first observed firm-year separately. We set $\alpha = 3$ and $\delta = 0.10$. When the lagged AI-capital stock is zero, we set $Q_{i0} = 1$ and $K_{i0} = V_{i0}$. The recursive marginal-Q equation is then applied from subsequent periods.

maintained assumptions of the capitalization framework; the parameter-sensitivity exercises assess robustness within this framework rather than testing those identifying assumptions.

[4] The results are robust to using alternative estimation windows, $[t-1, t+1]$ or $[t]$.

Section IA.5 examines alternative parameter values.

4.5. Validation

We conduct a series of validation exercises to assess whether the model-implied quantity of AI capital, K, captures economically meaningful firm-level variation in accumulated AI capabilities. Our validation therefore asks whether K is related to conventional measures of AI employment intensity ($ShareAI$) and complementary intangible inputs, and, more importantly, whether it contains information about subsequent AI investment beyond firms' contemporaneous AI employment intensity. We proceed in four steps. First, we decompose variation in $ShareAI$, K, and Q to distinguish persistent between-firm differences from within-firm variation over time. Second, we examine whether K is positively associated with AI-, data-, and IT-related labor intensity and with independently constructed measures of intangible capital. Third, we examine the industry distribution of estimated AI capital and whether it is concentrated in industries in which AI use would be expected to be more intensive. Finally, using job-posting data that are distinct from the employee data underlying the construction of K, we test whether K predicts firms' subsequent demand for AI-skilled labor after controlling for existing AI employment intensity and prior AI hiring activity.

4.5.1. Variance decomposition

Following Harford et al. (2025) and Hassan et al. (2019), we decompose the variance of $ShareAI$, K, and Q. Table IA1 reports the incremental adjusted R^2 from adding year, industry, and industry-year fixed effects. Panel A uses the full sample, and Panel B uses the sample with no missing controls as in Table 4. Across the measures, year, industry, and industry-year components jointly account for roughly 5–7% of the variation, leaving about 93–95% at the firm level. This evidence supports interpreting these proxies as primarily firm-level measures.

Firm-level variation, however, is distinct from persistent between-firm variation and within-firm variation over time. The variance decomposition results are consistent with the distinction between the quantity and price components of AI capital. In the full sample in Panel A, between-firm and within-firm variation account for 44.36% and 48.65% of the variation in $ShareAI$, respectively. For

K, the corresponding shares are 61.80% and 32.38%, indicating a more persistent between-firm component. In contrast, only 19.54% of the variation in Q is between firms, while 75.73% is within firms. In the sample with non-missing controls in Panel B, the between-firm component of K rises to 86.27%, while the within-firm component falls to 7.51%.

4.5.2. **AI-Skilled Employment**

We first examine whether the economic model preserves economically meaningful information contained in AI-skilled employment. If the model successfully extracts firms' underlying AI capital from the labor input, the resulting quantity measure should remain positively associated with AI-skilled employment. We therefore regress K on $ShareAI$ to examine whether the model-implied quantity of AI capital is reflected in firms' observable AI-skilled employment.

Column (1) of Panel A in Table **2** shows that K is positively associated with $ShareAI$. Both K and $ShareAI$ are standardized. A one-standard-deviation increase in $ShareAI$ is associated with a 0.1984-standard-deviation increase in K.

4.5.3. **Relevant Labor**

Related technical labor may also complement firms' accumulation and deployment of AI capital (Abis and Veldkamp, 2024; Tambe et al., 2020). We therefore examine whether K is associated with data-skilled and IT-skilled job-posting intensity, $ShareDataPost$ and $ShareITPost$, in addition to $ShareAI$.

Column (2) of Panel A in Table **2** shows that the coefficients on $ShareDataPost$ and $ShareITPost$ are statistically insignificant after controlling for $ShareAI$. Thus, the related-labor results do not provide strong incremental explanatory power beyond AI-skilled employment.

4.5.4. **Intangible Capital**

As AI capital shares important characteristics with other forms of intangible capital and is likely to coexist with them (Brynjolfsson et al., 2021), we further validate K using several intangible-capital proxies. $IntangCapital$ denotes total intangible capital, while $OrgCapital$ and $KnowCapital$ denote

its organizational- and knowledge-capital components, respectively, from Peters and Taylor (2017). *PatentCapital* denotes patent capital from Woeppel (2022).

Column (2) of Panel B in Table **2** includes all intangible-capital proxies jointly with *ShareAI*. *OrgCapital* has the strongest incremental association with K: a one-standard-deviation increase in *OrgCapital* is associated with a 0.1803-standard-deviation increase in K. *PatentCapital* is associated with only a 0.0700-standard-deviation increase in K whereas *IntangCapital* and *KnowCapital* are not statistically significant.

4.5.5. **The distribution of AI capital measures**

Figure 1 plots the yearly and Fama–French 12 industry averages of *ShareAI*, K, and Q. Both *ShareAI* and K increase substantially over the sample period. Their industry averages are highest in business equipment and telecommunications, consistent with AI-related activity being concentrated in these industries. The shadow-price measure, Q, also rises over time but displays substantially less cross-industry variation.

4.5.6. **Predictive Validation Using Subsequent AI Hiring Demand**

We further validate our AI capital measure using job-posting data that are distinct from the résumé data underlying the AI-employment measure. If K captures accumulated AI capabilities rather than contemporaneous AI employment alone, it should predict future AI hiring demand beyond the firm's existing AI workforce. The dependent variable, *ShareAIPost*, is the share of job postings seeking AI-related skills. We additionally control for lagged AI-job-posting intensity and the shares of IT- and data-related job postings, *ShareITPost* and *ShareDataPost*.

Table **3** shows that lagged AI capital positively predicts subsequent AI hiring intensity. The relation remains statistically significant after controlling for existing AI employment, prior AI hiring demand, and broader IT- and data-related hiring demand, and it persists with firm fixed effects.

The results provide external predictive validation of K: the measure contains information about firms' subsequent demand for AI-skilled labor beyond contemporaneous AI employment and prior AI hiring activity. They are also consistent with complementarity between accumulated AI capabilities

and additional AI-skilled labor, which we examine further in the acquisition setting.

5. AI Capital and Firms' Acquisitiveness

5.1. AI Capital and Acquisition Likelihood

We begin by testing **Prediction 1**. To test the relation between AI capital and firms' acquisitiveness, we run the following linear probability model (LPM) regressions:

$$MnA_{it} = \beta_0 + \beta_1 K_{i,t-1} + \beta_2 Controls_{i,t-1} + u_{it} \tag{4}$$

where MnA is a dummy equal to one if a firm announces an M&A deal as a bidder in a given year. K denotes the model-implied AI capital.[5]

Consistent with Prediction 1, Table 4 shows that firms with greater AI capital are more likely to bid. K is standardized. Column (3) indicates that a one-standard-deviation increase in K_{L1} is associated with a 2.21-percentage-point increase in the probability of becoming a bidder. This magnitude equals 9.34% of the unconditional acquisition rate of 23.66%.

5.2. Incremental Information in AI Capital

The baseline relation could simply reflect the big-data labor used to deploy AI or broader intangible capabilities that are shown to be correlated with AI capital in Table 2. We therefore examine whether AI capital contains incremental information about acquisition activity beyond these related firm characteristics.

Consistent with the distinction between AI investment and AI capital, Table IA4 shows that the positive relation between $ShareAI$ and acquisition activity becomes insignificant once firm fixed effects are included, whereas K remains significant in the baseline firm fixed-effects specification. We

[5]Logit, probit, and linear probability models yield qualitatively and quantitatively similar conclusions. Results are similar when explanatory variables are lagged by two years. Unless otherwise stated, "Controls" means the same set of control variables, except Table A4 includes additional deal-level controls; "Year FE" means the year fixed effect; "Industry FE" means the Fama–French 48 industry groups of the company; and "Firm FE" means the firm fixed effect. We do not include recent acquisition realizations as baseline controls. Because AI capital is persistent, acquisitions undertaken in prior years may themselves reflect earlier realizations of the same AI-capital-induced acquisitiveness that we seek to measure. Conditioning on recent acquisition activity would therefore change the estimate from the overall relation between accumulated AI capital and firms' acquisition propensity to the incremental relation conditional on previous acquisition realizations. Firm fixed effects instead absorb persistent time-invariant differences across firms in their underlying propensity to undertake acquisitions.

next provide a more direct test by including K and related labor and intangible-capital measures jointly in the same regression. Table 5 reports the results. Column (1) controls for $ShareAI$, $ShareDataPost$, and $ShareITPost$. The coefficient on K remains positive and significant, while none of these labor-based measures is statistically significant. Column (2) controls for total intangible capital, organizational capital, patent capital, and knowledge capital. Organizational and knowledge capital are significantly positive, while total intangible capital and patent capital are insignificant. The coefficient on K remains significantly positive. Column (3) includes the labor and intangible-capital measures jointly. In this specification, K remains significantly positive; organizational and patent capital are no longer significant, while knowledge capital is positive and significant at the 10% level. Across the three specifications, the estimated coefficient on K ranges from 1.70 to 3.20 percentage points, compared with the baseline firm-fixed-effects estimate of 2.21 percentage points.

The results indicate that K contains information beyond observable AI employment or broader organizational and technological capabilities. This incremental explanatory content is consistent with K capturing the accumulated stock of firms' AI-related productive capabilities.

5.3. Firm-Size Heterogeneity

We next test **Prediction 2** by examining whether the AI–acquisition relation differs across firm size. We define *Large* as an indicator equal to one for observations in the top quarter of the pooled distribution of firm size and zero for observations in the bottom quarter, excluding the middle half of the distribution. Firm size is measured alternatively by market capitalization and total employment. Under this specification, the coefficient on K_{L1} captures its marginal effect among small firms, while the interaction between K_{L1} and *Large* captures the difference in this effect between large and small firms.

Figure 2 shows that AI capital is concentrated among firms with high market capitalization. Columns (1) and (2) of Table 6 show significant cross-sectional size heterogeneity. The interaction between standardized AI capital and the large-firm indicator is 0.0463 when size is measured by market capitalization and 0.1567 when size is measured by total employment; both estimates are statistically significant. Columns (3) and (4) introduce firm fixed effects. The interaction coefficients

remain positive, at 0.0521 and 0.0349, respectively, but neither is statistically significant. Thus, the evidence for a stronger AI–acquisition relation among large firms is concentrated in the cross section rather than within firms over time.

Taken together, the results support size heterogeneity primarily as a persistent cross-sectional feature: AI capital is concentrated among large firms, and the cross-sectional association between AI capital and acquisitions is stronger among larger firms.

6. Endogeneity and Identification

Having established a statistical association between AI capital and merger activity, we next use an instrumental-variable design to address two key identification concerns: reverse causality, whereby potential bidders may accumulate more AI capital in anticipation of future acquisitions, and omitted variables, whereby unobserved firm characteristics may affect both AI-capital accumulation and merger activity.

We employ instrumental-variable two-stage-least-squares (IV-2SLS) regressions. Our instrument, $AIExposure_{2010}$, captures a firm's historical connection before 2010 to universities with strong AI programs. This predetermined exposure predicts firms' subsequent ability to accumulate AI capital and predates the acceleration of commercial AI investment around 2012. The identifying assumption is that, conditional on the included firm characteristics, industry and year fixed effects, and the additional university-exposure controls, historical exposure to AI-intensive universities affects subsequent acquisition activity primarily through firms' accumulation of AI capital.

Table 7 reports the 2SLS results. Column (1) reports the first stage. The coefficient on $AIExposure_{2010}$ is 0.1009 and is significant at the 1% level, and the reported first-stage F-statistic is 27.4320. Column (2) reports the second stage. The coefficient on $\widehat{K}_{L1}^{SD}$ is 0.2259 and is significantly positive at the 5% level. The IV estimate therefore preserves the positive sign of the baseline relation but is larger than the corresponding baseline estimate of 0.0221. As the IV and baseline specifications identify the relation from different sources of variation, we do not interpret the difference in point estimates as evidence about the magnitude of a homogeneous treatment effect. Instead, we view the IV evidence as complementary evidence that the positive AI-capital–acquisition relation is also

present when AI capital is instrumented using firms' pre-2010 exposure to AI-intensive universities.

7. Mechanisms

This section tests Predictions 3 and 4. We first examine whether acquirers with greater AI capital select targets with more AI-skilled labor, both in realized deals and relative to matched potential alternatives. We next examine whether financing conditions affect the strength of the relation between AI capital and acquisition activity. Section IA.3 evaluates the competing interpretations developed in Section *2.5*.

7.1. Acquisition of AI Human Capital

We first test **Prediction 3**, which predicts that firms with greater AI capital are more likely to acquire complementary AI human capital. Table **3** already shows that greater AI capital predicts firms' subsequent internal demand for AI-skilled labor. We now examine whether this complementarity also shapes the selection of acquisition targets.

We begin with realized acquisitions. Table **8** reports estimates from:

$$AITarget_d = \beta_0 + \beta_1 K_d + \beta_2 Controls_d + u_d, \tag{5}$$

where $AITarget_d$ is measured either by the target's share of AI-skilled employees ($ShareAI_T$) or by an indicator equal to one if $ShareAI_T$ is positive ($ShareAID_T$). K_d denotes the acquirer's AI capital before the deal announcement. $ShareAI$ and K are standardized. $Controls$ denotes the set of control variables reported in Panel B of Table **1** for deal and acquirer characteristics. The realized-deal estimates indicate that acquirers with greater AI capital tend to acquire targets with greater AI human capital. In the specifications with controls, a one-standard-deviation increase in K_d is associated with a 0.3902-standard-deviation increase in the target's AI-employee share and a 14.10-percentage-point increase in the probability that the target employs AI-skilled workers.

We next sharpen this interpretation using potential acquirer–target pairs. For each realized transaction, we identify five comparable potential acquirers and five comparable targets using progressively richer matching criteria based on industry and firm characteristics. The matching pro-

cedure retains 144 realized deals with sufficient matched firms. The comparison set combines the actual acquirer with matched potential targets and matched potential acquirers with the actual target. The dependent variable equals one for the realized pair and zero for a matched potential pair. All specifications include deal fixed effects to identify within-deal differences between the realized pair and its matched alternatives. This design helps distinguish complementarity in pair formation from differences in the types of firms that participate in M&A.

Table 9 reports results. Panel A uses the full set of potential acquirer–target pairs. Across all matching procedures, the interaction between acquirer AI capital and $ShareAI_T$ is positive. The extensive-margin interactions are positive and statistically significant across all three matching procedures: the interaction between acquirer AI capital and $ShareAID_T$ ranges from 0.0245 to 0.0368. Thus, realized pairs are more likely than otherwise similar potential pairs to combine an AI-intensive acquirer with an AI-intensive target.

Panel B conditions on the realized acquirer and compares the actual target with matched potential targets. This specification asks whether, given the acquirer that actually undertook the acquisition, acquirers with greater AI capital are more likely to select targets employing AI-skilled workers. The interaction between acquirer AI capital and target $ShareAI_T$ remains positive, with coefficients ranging from 0.0145 to 0.0209. The extensive-margin estimates are more precisely estimated. A one-standard-deviation increase in acquirer AI capital increases the differential probability of selecting a target with AI-skilled employees, relative to a target without AI-skilled employees, by 5.4 to 8.1 percentage points across the alternative matching procedures. The interaction estimates support a complementarity interpretation. Target AI employee intensity by itself is not positively associated with realization at the mean level of acquirer AI capital, whereas the interaction with acquirer AI capital is consistently positive, indicating that the relative attractiveness of AI-intensive targets rises with the AI capital of the acquirer.

Taken together, the realized-deal and matched-pair evidence shows that firms with greater AI capital disproportionately select targets with complementary AI human capital.

7.2. Financing Costs

We next test **Prediction 4** by examining whether the AI–acquisition relation is weaker under higher financing costs:

$$MnA_{it} = \beta_0 + \beta_1 K_{i,t-1} + \beta_2 Mecha_{i,t-1} + \beta_3 K_{i,t-1} \times Mecha_{i,t-1} + \beta_4 Controls_{i,t-1} + u_{it} \quad (6)$$

where $Mecha$ denotes a financing-cost measure. We use the cost of equity (CoE) and the cost of debt (CoD), where higher values indicate less favorable financing conditions.

Table **A3** reports the results. The interaction between AI capital and financing costs is negative for both measures. The coefficient on $K_{L1}^{SD} \times CoE_{L1}^{SD}$ is -0.0123 and is significant at the 5% level, while the coefficient on $K_{L1}^{SD} \times CoD_{L1}^{SD}$ is -0.0138 and is significant at the 1% level. Thus, the positive relation between AI capital and acquisition activity becomes weaker as financing costs increase.

Taken together, the results are consistent with financing conditions affecting the strength of the AI-capital–acquisition relation.

8. AI Capital and Deal-Level Outcomes

Having established that AI-rich bidders select targets with complementary AI human capital, we next examine additional characteristics and outcomes of their acquisitions. Table **A4** presents results of:

$$Outcome_d = \beta_0 + \beta_1 K_d + \beta_2 Controls_d + u_d \quad (7)$$

where $Outcome$ denotes the deal-level outcome for deal d, as indicated under column numbers. K_d denotes the acquirer's AI capital before the deal announcement. $Controls$ denotes the set of deal and acquirer characteristics reported in Panel B of Table **1**, excluding variables that are constant by construction in the public-to-public sample. In each specification, we exclude the corresponding dependent variable from the control set to avoid perfect prediction.

Consistent with a capability-building interpretation, bidders with greater AI capital acquire targets that are smaller relative to the acquirer, as reflected in the negative relation between K and relative deal size. At the same time, we do not find affirmative evidence that AI-rich bidders systematically overpay or undertake value-destroying acquisitions: K is not significantly associated

with offer premiums, bidder announcement returns, target announcement returns, or bidder long-run returns.

9. Additional Analyses and Robust Checks

9.1. Additional Analyses

We report several additional analyses in the Internet Appendix. Section IA.3 evaluates the competing interpretations developed in Section *2.5*. Section IA.4.1 compares the baseline quantity measure K with alternative AI-related measures and shows that $ShareAI$ and Q lose statistical significance once firm fixed effects are included. Section IA.4.2 examines whether firms' own AI measures predict their unconditional likelihood of becoming acquisition targets.

9.2. Robustness Checks

We also conduct additional robustness tests in the Internet Appendix. Section IA.5.1 shows that the baseline relation remains robust after controlling for alternative measures of firms' data assets. Section IA.5.2 shows that the baseline results remain robust to alternative firm-size restrictions, including excluding the largest firms and trimming both tails of the market-capitalization distribution, and to a logarithmic transformation of AI capital. Section IA.5.3 examines industry-by-year fixed effects and pre-sample acquisition history. Section IA.5.4 examines sensitivity of the estimated AI-capital measures to alternative model parameters.

10. Conclusion

This paper examines how accumulated AI capabilities are associated with firms' participation in the market for corporate control during the diffusion of AI. We develop a framework in which AI capital is associated with greater expansion through acquisitions, with the relation expected to be particularly important among large incumbents. To test these predictions, we construct firm-year measures of AI capital by combining AI-skilled employment with a dynamic capital-accumulation model. Unlike measures based solely on AI employment or adoption, our approach treats AI as a durable, firm-specific intangible asset and separately estimates the model-implied quantity and price

of AI capital.

The empirical evidence supports the main predictions, with some qualifications. Firms with greater AI capital are more likely to become acquirers. The AI–acquisition relation is stronger among large firms in the cross section. AI capital also predicts subsequent demand for AI-skilled labor beyond existing AI employment and prior AI hiring activity, providing external predictive validation of the measure. The AI-capital–acquisition relation is also weaker when firms face higher financing costs, consistent with financing conditions affecting firms' ability to act on acquisition opportunities. Consistent with complementarity between installed AI capabilities and additional AI expertise, bidders with greater AI capital acquire targets employing more AI-skilled workers. Matched potential-pair tests further show that this relation reflects differential target selection: conditional on the realized acquirer, AI-intensive targets become relatively more likely to be selected as acquirer AI capital rises. AI-rich bidders also tend to undertake acquisitions with smaller deal values relative to their own size, while we do not detect significantly higher offer premiums or significantly lower announcement or long-run returns. The additional tests provide no affirmative evidence that defensive acquisitions, positioning motives, equity misvaluation, or managerial agency problems are primary explanations for the baseline relation.

The findings have two broader implications. First, the measurement framework illustrates how observable AI investment and market valuation can be combined to estimate an economically meaningful stock of intangible AI capital that is not recognized in financial statements. The predictive relation between AI capital and subsequent AI hiring further indicates that the resulting measure contains information beyond contemporaneous AI employment. Second, the results identify acquisitions as one way in which firms extend accumulated AI capabilities beyond their existing organizational boundaries. Both realized deal and matched-pair evidence show that this expansion is directed toward targets with complementary AI human capital. As AI capital is concentrated among large firms and the cross-sectional AI–acquisition relation is stronger among larger firms, this form of inorganic expansion may contribute to the persistence of incumbent advantage.

Several questions remain for future research. We do not examine the long-run effects of AI-related acquisitions on competition, innovation, productivity, or labor outcomes. Nor do we observe how

acquired AI capabilities are integrated within the bidder after deal completion. Future work could examine whether AI-related acquisitions generate durable productivity gains, accelerate subsequent innovation, or affect the allocation and mobility of AI-skilled labor across firms. Because target-side AI measures are available only for public firms, the target-selection evidence does not directly speak to private-target acquisitions, which constitute the majority of deals in the SDC sample. Extending the analysis to private targets would be particularly useful for assessing whether the same complementarity operates in acquisitions of smaller AI-intensive firms and startups. More broadly, as AI becomes increasingly embedded in firms' production and organizational processes, understanding how accumulated AI capabilities interact with firm boundaries remains an important area for research.

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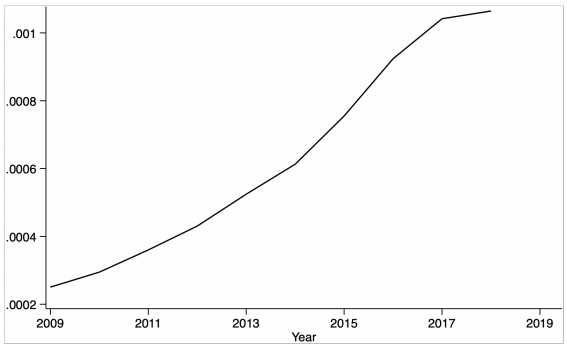
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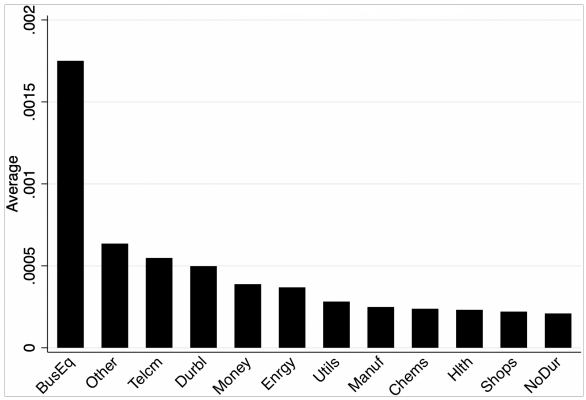
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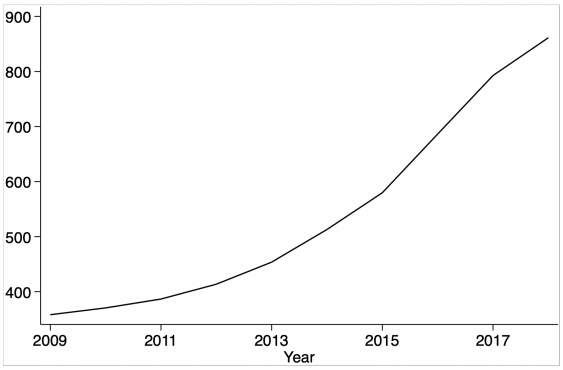
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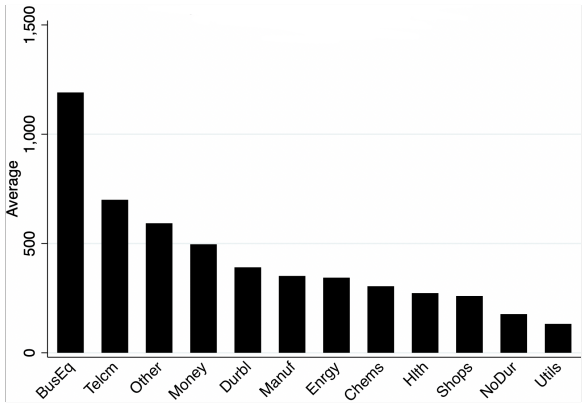
(a) *ShareAI*: Yearly average



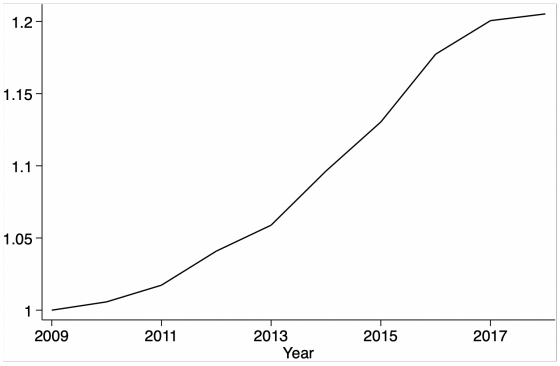
(b) *ShareAI*: Industry average



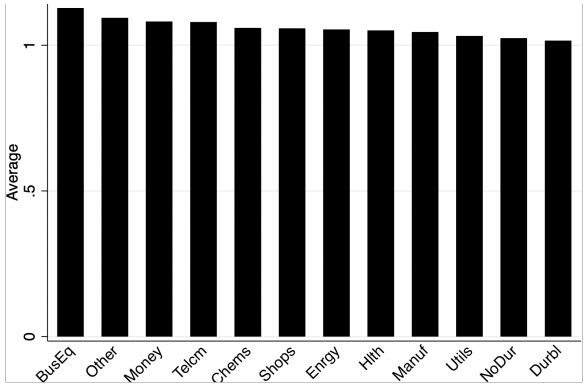
(c) K: Yearly average



(d) K: Industry average

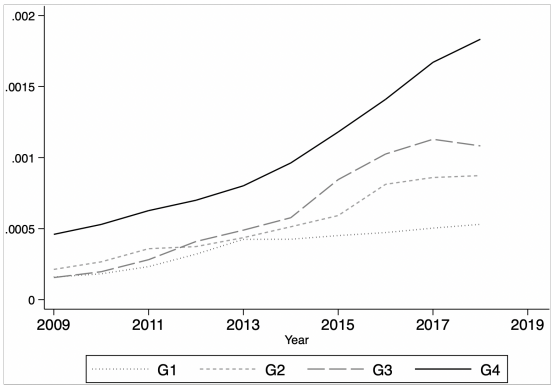


(e) Q: Yearly average

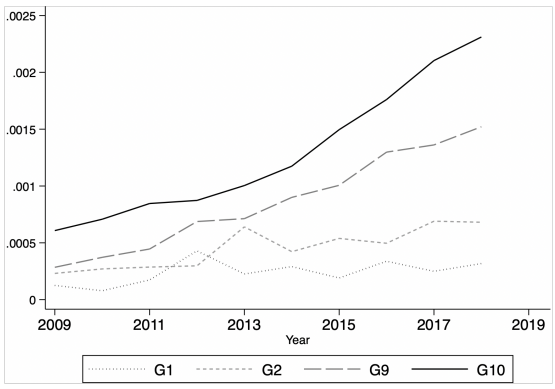


(f) Q: Industry average

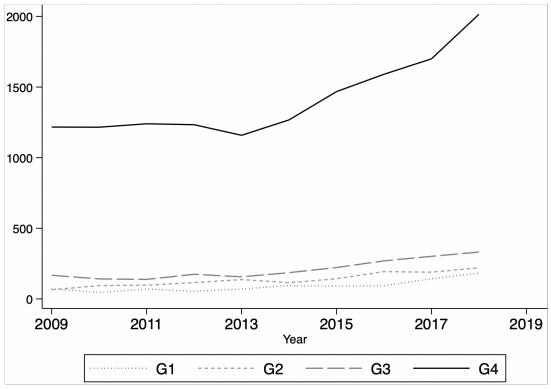
Figure 1: Average *ShareAI*, K, and Q over Time and across Industries. This figure plots yearly averages and Fama–French 12 industry averages of *ShareAI*, AI capital quantity (K), and the model-implied shadow price of AI capital (Q). For each variable, the left-hand panel reports the yearly average and the right-hand panel reports the industry average. K is measured in millions of U.S. dollars, and Q is unitless. *ShareAI* is a fraction of total employment.



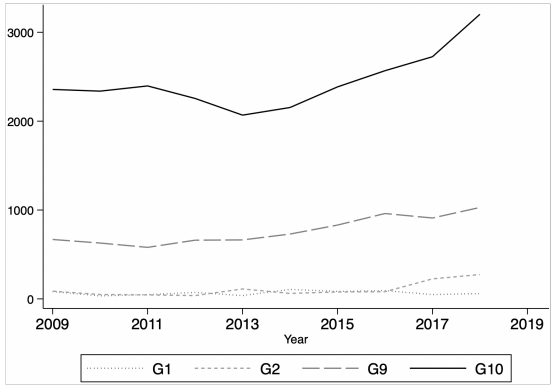
(a) *ShareAI*: 4 groups



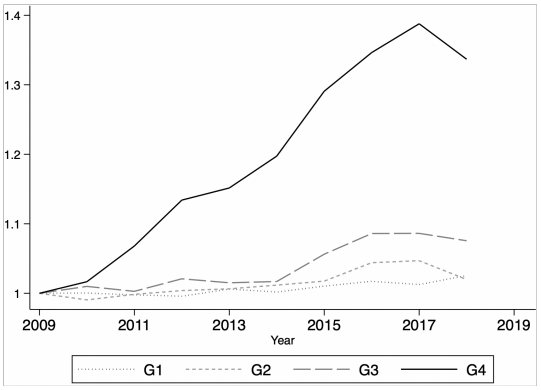
(b) *ShareAI*: 10 groups



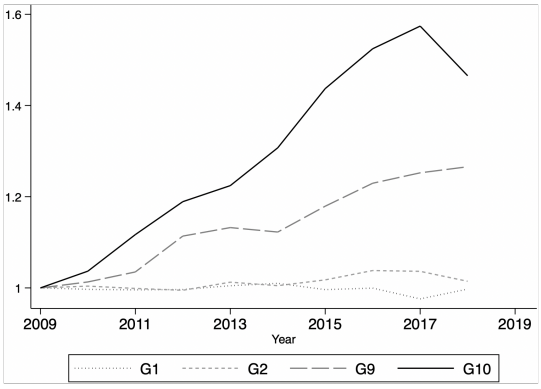
(c) K: 4 groups



(d) K: 10 groups



(e) Q: 4 groups



(f) Q: 10 groups

Figure 2: Average *ShareAI*, K, and Q by Market-Value Group. This figure plots yearly averages of *ShareAI*, K, and Q across market-value groups. The left-hand panels divide firms into four market-value groups. The right-hand panels form market-value deciles and display G1, G2, G9, and G10 for readability. G1 contains the smallest firms. K is measured in millions of U.S. dollars, Q is unitless, and *ShareAI* is plotted as a fraction of total employment.

Table 1: Summary Statistics

This table presents summary statistics, including the number of observations, mean, standard deviation, 10th percentile, 25th percentile, median, 75th percentile, and 90th percentile. *Size* is measured in billions of U.S. dollars, while K is measured in millions. CAR, CAR_T, *Premium*, $BHAR$, and *Runup* are reported in percentage points. All variables are defined in Table **A1**. Panel A presents the Compustat data sample, and Panel B presents the SDC deal sample.

Panel A: Summary statistics: Compustat sample									
Variable	NObs	Mean	SD	P10	P25	Median	P75	P90	Winsorized
$MnA\%$	15671	23.66	42.50	0.00	0.00	0.00	0.00	100.00	N
$ShareAI\%$	15671	0.06	0.19	0.00	0.00	0.00	0.00	0.16	Y
K	15671	557.96	1637.45	0.00	0.00	0.00	172.19	1391.64	Y
Q	15671	1.06	0.35	1.00	1.00	1.00	1.00	1.28	Y
$Size$	12804	4.87	10.09	0.06	0.23	0.94	3.71	13.61	Y
ROA	15650	0.07	0.25	-0.07	0.06	0.11	0.16	0.22	Y
$Leverage$	15591	0.23	0.24	0.00	0.03	0.19	0.34	0.50	Y
$TobinQ$	12036	2.06	1.56	0.92	1.15	1.55	2.37	3.77	Y
$SalesGrowth$	15563	0.08	0.48	-0.15	-0.02	0.02	0.12	0.28	Y
$ProfitMargin$	15554	-0.41	4.48	-0.06	0.05	0.12	0.21	0.33	Y
M/B	12803	3.09	5.02	0.73	1.25	2.10	3.73	6.61	Y
$Volatility$	14851	0.44	0.25	0.21	0.27	0.38	0.53	0.72	Y
$PastReturn$	14851	0.20	0.54	-0.32	-0.09	0.13	0.38	0.74	Y
Panel B: Summary statistics: SDC sample									
Variable	NObs	Mean	SD	P10	P25	Median	P75	P90	Winsorized
CAR	2178	0.92	5.57	-3.97	-1.36	0.45	2.79	6.58	Y
CAR_T	316	29.18	25.90	2.46	9.69	25.02	38.74	59.35	Y
$Premium$	419	48.37	43.97	11.11	23.60	37.66	60.93	103.53	Y
$BHAR$	1982	-0.08	33.75	-40.27	-19.87	-2.08	17.05	37.89	Y
Control variables									
$RelSize$	2178	0.16	0.35	0.00	0.01	0.05	0.15	0.41	Y
$Earnout$	2178	0.14	0.34	0.00	0.00	0.00	0.00	1.00	N
$Tender$	2178	0.06	0.24	0.00	0.00	0.00	0.00	0.00	N
$FullStock$	2178	0.02	0.15	0.00	0.00	0.00	0.00	0.00	N
$FullCash$	2178	0.64	0.48	0.00	0.00	1.00	1.00	1.00	N
$Private$	2178	0.76	0.43	0.00	1.00	1.00	1.00	1.00	N
$Subsidiary$	2178	0.03	0.16	0.00	0.00	0.00	0.00	0.00	N
$Diversified$	2178	0.42	0.49	0.00	0.00	0.00	1.00	1.00	N
$Hostile$	2178	0.00	0.06	0.00	0.00	0.00	0.00	0.00	N
$NBidders$	2178	0.02	0.13	0.00	0.00	0.00	0.00	0.00	N
$Toehold$	2178	0.02	0.15	0.00	0.00	0.00	0.00	0.00	N
ROA	2178	0.04	0.12	-0.03	0.02	0.06	0.09	0.12	Y
$TobinQ$	2178	2.10	1.24	1.06	1.33	1.76	2.41	3.55	Y
$Leverage$	2178	0.21	0.17	0.00	0.06	0.20	0.31	0.45	Y
M/B	2178	3.42	3.82	1.03	1.62	2.50	4.04	6.50	Y
$Runup$	2178	15.49	29.39	-17.86	0.02	14.92	30.97	49.32	Y
$Size$	2178	18.14	46.71	0.18	0.61	1.94	9.82	44.86	Y

Table 2: Validation of the AI Capital K

This table reports the relation between the model-implied quantity of AI capital, K, and other relevant measures. The dependent variable is K. *ShareAI*, *ShareDataPost*, and *ShareITPost* are AI-skilled employment, data-related job postings, and IT-skilled job postings, respectively, from Babina et al. (2024). *IntangCapital*, *OrgCapital*, and *KnowCapital* denote intangible capital, organizational capital, and knowledge capital, respectively, as provided by Peters and Taylor (2017). *PatentCapital* denotes patent capital from Woeppel (2022). A superscript ^{SD} means the variable is standardized. Control variables are those in Table 4. See the variable definitions in Table A1. Numbers in parentheses are t-statistics based on standard errors clustered by firm. ***, **, and * denote the significance levels of 1%, 5%, and 10%, respectively.

Panel A: AI Employment and AI Capital		
	(1)	(2)
Y:	K^{SD}	K^{SD}
$ShareAI^{SD}$	0.1984***	0.2109***
	(14.4073)	(14.2102)
$ShareDataPost^{SD}$		0.0083
		(1.4721)
$ShareITPost^{SD}$		-0.0067
		(-1.0081)
Controls	Y	Y
Year FE	Y	Y
Firm FE	Y	Y
NObs	11672	9079
Adj. R^2	0.9547	0.9526
Panel B: Validation Using Alternative Intangible-Capital Measures		
	(1)	(2)
Y:	K^{SD}	K^{SD}
$ShareAI^{SD}$		0.1941***
		(14.6810)
$IntangCapital^{SD}$	-0.0556	-0.0424
	(-0.3894)	(-0.3307)
$OrgCapital^{SD}$	0.2188*	0.1803*
	(1.8334)	(1.7092)
$PatentCapital^{SD}$	0.0734*	0.0700**
	(1.9589)	(2.0914)
$KnowCapital^{SD}$	0.1229	0.0804
	(1.3405)	(0.9937)
Controls	Y	Y
Year FE	Y	Y
Firm FE	Y	Y
NObs	11672	11672
Adj. R^2	0.9435	0.9560

Table 3: Predictive Validation of AI Capital: Subsequent AI Hiring Demand

This table examines whether firms with greater AI capital subsequently exhibit greater demand for AI-skilled labor. The dependent variable in all columns is the share of AI-related job postings ($ShareAIPost$) in year t. K denotes the model-implied AI capital. $ShareAI$ denotes the share of AI-skilled employees. $ShareAIPost$, $ShareITPost$, and $ShareDataPost$ denote the shares of AI-skilled, IT-skilled, and data-related job postings, respectively, from Babina et al. (2024). Control variables are those in Table 4. A subscript $L1$ indicates a one-year lag, and a superscript SD indicates standardization. Industry fixed effects are used in Columns (1)–(3), while firm fixed effects are used in Columns (4)–(6). See the variable definitions in Table A1. Numbers in parentheses are t-statistics based on standard errors clustered by firm. ***, **, and * denote the significance levels of 1%, 5%, and 10%, respectively.

Y: $ShareAIPost^{SD}$	(1)	(2)	(3)	(4)	(5)	(6)
K^{SD}_{L1}	0.3854***	0.0648***	0.0610***	0.2644***	0.0879***	0.0908***
	(6.7910)	(3.7046)	(3.5278)	(13.6184)	(4.3279)	(4.2080)
$ShareAI^{SD}_{L1}$		0.1293***	0.1260***		0.1329***	0.1278***
		(6.3103)	(6.1123)		(4.8877)	(4.8205)
$ShareAIPost^{SD}_{L1}$		0.7135***	0.7041***		0.4628***	0.4533***
		(21.9713)	(21.0664)		(5.1102)	(5.3056)
$ShareITPost^{SD}_{L1}$			0.0515***			0.0303
			(3.8446)			(1.2745)
$ShareDataPost^{SD}_{L1}$			-0.0118			-0.0045
			(-0.7637)			(-0.2223)
Controls	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y
Industry FE	Y	Y	Y	N	N	N
Firm FE	N	N	N	Y	Y	Y
NObs	8849	7801	7755	8849	7801	7755
Adj. R^2	0.2724	0.6600	0.6598	0.5771	0.6931	0.6926

Table 4: AI Capital and Acquisition Likelihood

This table reports the relation between firms' AI capital and the likelihood of becoming a bidder in the following year using the following linear probability model (LPM):

$$MnA_{it} = \beta_0 + \beta_1 K_{i,t-1} + \beta_2 Controls_{i,t-1} + u_{it}$$

MnA is a dummy equal to one if a firm i announces an M&A deal as an acquirer in a year t. K denotes the model-implied AI capital. A subscript $_{L1}$ means the variable is lagged for one year. A superscript ^{SD} means the variable is standardized. See the variable definitions in Table **A1**. Numbers in parentheses are t-statistics based on standard errors clustered by firm. ***, **, and * denote the significance levels of 1%, 5%, and 10%, respectively.

Y: MnA	(1)	(2)	(3)
K^{SD}_{L1}	0.0781***	0.0237**	0.0221***
	(10.5834)	(2.4345)	(3.4004)
$Size_{L1}$		0.0063***	0.0058***
		(7.2681)	(11.7546)
ROA_{L1}		0.0664***	0.0866***
		(3.3319)	(3.8991)
$Leverage_{L1}$		0.0247	-0.0729
		(1.0815)	(-1.3140)
$TobinQ_{L1}$		-0.0109***	-0.0006
		(-3.0019)	(-0.1132)
$SalesGrowth_{L1}$		0.0052	-0.0063
		(0.8394)	(-1.1747)
$ProfitMargin_{L1}$		0.0000	0.0007
		(0.0476)	(1.2595)
M/B_{L1}		0.0006	0.0001
		(0.7477)	(0.0969)
$Volatility_{L1}$		-0.2646***	-0.1045***
		(-10.4395)	(-3.0444)
$PastReturn_{L1}$		0.0426***	0.0293***
		(6.5134)	(3.6056)
Constant	0.2358***	0.3389***	0.2734***
	(21.3800)	(19.4654)	(19.7800)
Controls	N	Y	Y
Year FE	N	Y	Y
Industry FE	N	Y	N
Firm FE	N	N	Y
NObs	15671	11350	11350
Adj. R^2	0.0346	0.0985	0.2625

Table 5: Incremental Information in AI Capital

This table reports robustness tests for the baseline regression that additionally control for related labor and intangible-capital measures examined in Table 2. The dependent variable, MnA, is a dummy equal to one if a firm i announces an M&A deal as an acquirer in year t. The independent variable is K. $ShareAI$, $ShareDataPost$, and $ShareITPost$ are AI-skilled employment, data-skilled job postings, and IT-skilled job postings, respectively, from Babina et al. (2024). $IntangCapital$, $OrgCapital$, and $KnowCapital$ denote total intangible capital, organizational capital, and knowledge capital, respectively, from Peters and Taylor (2017). $PatentCapital$ denotes patent capital from Woeppel (2022). A subscript $_{L1}$ means the variable is lagged for one year. A superscript ^{SD} means the variable is standardized. See the variable definitions in Table A1. Control variables are those in Table 4. Numbers in parentheses are t-statistics based on standard errors clustered by firm. ***, **, and * denote the significance levels of 1%, 5%, and 10%, respectively.

Y: MnA	(1)	(2)	(3)
K^{SD}_{L1}	0.0320***	0.0170**	0.0220***
	(6.8944)	(2.2386)	(3.4175)
$ShareAI^{SD}_{L1}$	-0.0069		-0.0044
	(-0.6130)		(-0.4034)
$ShareDataPost^{SD}_{L1}$	0.0101		0.0096
	(1.3906)		(1.3595)
$ShareITPost^{SD}_{L1}$	-0.0052		-0.0032
	(-0.7182)		(-0.4161)
$IntangCapital^{SD}_{L1}$		-0.0215	0.0080
		(-0.7767)	(0.4419)
$OrgCapital^{SD}_{L1}$		0.0408*	0.0161
		(1.8129)	(1.0704)
$PatentCapital^{SD}_{L1}$		0.0069	0.0053
		(1.4352)	(0.8080)
$KnowCapital^{SD}_{L1}$		0.0120**	0.0133*
		(2.0519)	(1.8473)
Controls	Y	Y	Y
Year FE	Y	Y	Y
Firm FE	Y	Y	Y
NObs	7961	11350	7961
Adj. R^2	0.2561	0.2632	0.2569

Table 6: Firm Size and the AI–Acquisition Relation

This table examines whether the relation between AI capital and the likelihood of becoming a bidder varies with firm size using the following model:

$$MnA_{it} = \beta_0 + \beta_1 K_{i,t-1} + \beta_2 Large_{i,t-1} + \beta_3 (K_{i,t-1} \times Large_{i,t-1}) + \beta_4 Controls_{i,t-1} + u_{it}$$

MnA is a dummy equal to one if a firm i announces an M&A deal as an acquirer in a year t. K denotes the model-implied AI capital. $Large$ is an indicator equal to one for observations in the top quarter of the pooled distribution of firm size and zero for observations in the bottom quarter, excluding the middle. Firm size is measured alternatively by market capitalization ($MktCap$) or total employment ($TotalEmployees$). A subscript $_{L1}$ means the variable is lagged for one year. A superscript ^{SD} means the variable is standardized. Control variables are those in Table 4. See the variable definitions in Table A1. Numbers in parentheses are t-statistics based on standard errors clustered by firm. ***, **, and * denote the significance levels of 1%, 5%, and 10%, respectively.

Y: MnA	(1)	(2)	(3)	(4)
Size:	$Log(MktCap)$	$TotalEmployees$	$Log(MktCap)$	$TotalEmployees$
K_{L1}^{SD}	-0.0265*	-0.1410**	-0.0321	-0.0124
	(-1.6495)	(-2.5072)	(-0.5063)	(-0.2669)
$Large_{L1}$	0.2520***	0.2105***	0.1659***	0.1340***
	(7.6879)	(7.3414)	(7.6170)	(4.7277)
$K_{L1}^{SD} \times Large_{L1}$	0.0463**	0.1567***	0.0521	0.0349
	(2.4352)	(2.7295)	(0.8456)	(0.7486)
Controls	Y	Y	Y	Y
Year FE	Y	Y	Y	Y
Industry FE	Y	Y	N	N
Firm FE	N	N	Y	Y
NObs	5351	4988	5191	4912
Adj. R^2	0.1707	0.1703	0.3001	0.3170

Table 7: Instrumental Variable Estimates

This table reports the 2SLS results using $AIExposure_{2010}$ as the instrumental variable (IV). MnA is a dummy equal to one if a firm i announces an M&A deal as an acquirer in a year t. K denotes the model-implied AI capital. $AIExposure_{2010}$ is firms' ex-ante exposure to AI universities. Following Babina et al. (2024), the specifications additionally control for firms' ex-ante exposure to universities that are strong in computer-science research and to top-10 universities. A subscript $_{L1}$ means the variable is lagged for one year. A superscript ^{SD} means the variable is standardized. Control variables are those in Table 4. See the variable definitions in Table A1. Numbers in parentheses are t-statistics based on standard errors clustered by firm. ***, **, and * denote the significance levels of 1%, 5%, and 10%, respectively.

	First Stage	Second Stage
	(1)	(2)
Y:	K_{L1}^{SD}	MnA
$\widehat{K}_{L1}^{SD}$		0.2259**
		(2.0738)
$AIExposure_{2010}$	0.1009***	
	(4.0191)	
University Controls	Y	Y
Controls	Y	Y
Year FE	Y	Y
Industry FE	Y	Y
NObs	11064	11064
F statistics	27.4320	–

Table 8: Acquisition of AI Human Capital: Realized deals

This table examines whether AI-rich acquirers tend to acquire targets with AI employees at the deal level. The sample is restricted to completed public-to-public acquisitions in which both the bidder and the target have non-missing AI measures. The dependent variable, indicated in each column heading, is either the target firm's AI-skilled employment ($ShareAI_T$) or an indicator equal to one if the target has a positive AI-skilled employment ($ShareAID_T$). K denotes the acquirer's AI capital measured before the deal announcement. A superscript ^{SD} means the variable is standardized. Controls are drawn from the deal and acquirer characteristics listed under "Control variables" in Panel B of Table 1, excluding variables that are constant by construction in the public-to-public sample. See the variable definitions in Table A1. Numbers in parentheses are t-statistics based on standard errors clustered by acquirer. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively. Industry fixed effects refer to the acquirer's Fama–French 48 industry.

	(1)	(2)	(3)	(4)
Y:	$ShareAI_T^{SD}$	$ShareAID_T$	$ShareAI_T^{SD}$	$ShareAID_T$
K^{SD}	0.3195***	0.1525***	0.3902**	0.1410**
	(2.8963)	(4.0701)	(2.0471)	(2.3334)
Controls	N	N	Y	Y
Year FE	N	N	Y	Y
Industry FE	N	N	Y	Y
NObs	193	193	193	193
Adj. R^2	0.0947	0.0958	0.1324	0.1976

Table 9: Acquisition of AI Human Capital: Potential Acquirer–Target Pairs

This table examines whether acquirer AI capital and target AI intensity are complementary in the formation of potential acquisition pairs. The candidate-pair sample is constructed by matching each realized deal to potential public acquirers and targets drawn from the corresponding industry-matched pool. "Ind-TA" matches firms within industry based on total assets; "Ind-TA-ROA" applies propensity-score matching within industry using total assets and ROA; and "Ind-TA-Controls" applies propensity-score matching within industry using the full set of matching covariates reported in Table 4 and total assets. Five nearest-neighbor firms are retained for each realized firm. Deals are retained if they have enough matched pairs. The matching procedure retains 144 realized deals with sufficient matched firms. The dependent variable, $RealPair$, equals one for the realized acquirer–target pair and zero for matched potential pairs. K_A^{SD} denotes the standardized AI capital of the acquirer. Target AI intensity, $TargetAI$, is measured alternatively by the standardized share of AI employees at the target firm ($ShareAI_T^{SD}$) and by an indicator equal to one if the target has a positive share of AI employees ($ShareAID_T$). Panel A includes the realized pair, pairs between the actual acquirer and matched potential targets, and pairs between matched potential acquirers and the actual target. Panel B restricts the sample to the realized pair and pairs between the actual acquirer and matched potential targets. Holding the acquirer fixed within each deal, the acquirer K_A^{SD} is absorbed by deal fixed effects. Acquirer and target controls consist of the same firm-level characteristics used in Table 4, entered separately for the acquirer and the target. We additionally control for a diversifying deal indicator (acquirer and target are not in the same 2-digit SIC industries), the relative total asset size (total assets of the acquirer over total assets of the target), and deal fixed effects. Continuous explanatory variables are standardized and indicated by ^{SD}. Numbers in parentheses are t-statistics based on standard errors clustered at the deal level. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Panel A. Potential Acquirer–Target Pairs

Matching Method:	Ind-TA		Ind-TA-ROA		Ind-TA-Controls	
	(1)	(2)	(3)	(4)	(5)	(6)
Target AI Employees Measure:	$ShareAI_T^{SD}$	$ShareAID_T$	$ShareAI_T^{SD}$	$ShareAID_T$	$ShareAI_T^{SD}$	$ShareAID_T$
K_A^{SD}	0.0002	-0.0055	-0.0050	-0.0140**	-0.0048	-0.0141**
	(0.0400)	(-0.9202)	(-0.9671)	(-2.2220)	(-1.0253)	(-2.1883)
Target AI	-0.0095	-0.0058	-0.0130*	-0.0309	-0.0107	-0.0185
	(-1.3534)	(-0.2893)	(-1.7048)	(-1.4370)	(-1.2438)	(-0.8406)
$K_A^{SD}\times$ Target AI Employees	0.0118**	0.0245**	0.0125*	0.0368***	0.0088*	0.0359***
	(2.3180)	(2.0493)	(1.6987)	(2.9749)	(1.7247)	(3.0086)
Acquirer and Target Controls	Y	Y	Y	Y	Y	Y
Deal Characteristics	Y	Y	Y	Y	Y	Y
Deal FE	Y	Y	Y	Y	Y	Y
Observations	1,584	1,584	1,584	1,584	1,584	1,584
Adj. R^2	0.0127	0.0127	0.0217	0.0240	0.0144	0.0177

Panel B. Potential Target Choice Conditional on the Acquirer

Matching Method:	Ind-TA		Ind-TA-ROA		Ind-TA-Controls	
	(1)	(2)	(3)	(4)	(5)	(6)
Target AI Employees Measure:	$ShareAI_T^{SD}$	$ShareAID_T$	$ShareAI_T^{SD}$	$ShareAID_T$	$ShareAI_T^{SD}$	$ShareAID_T$
Target AI	-0.0235*	-0.0419	-0.0264*	-0.0757*	-0.0271*	-0.0733
	(-1.8697)	(-1.0368)	(-1.9640)	(-1.7221)	(-1.7560)	(-1.6316)
$K_A^{SD}\times$ Target AI Employees	0.0208**	0.0536***	0.0209*	0.0676***	0.0145	0.0809***
	(2.5843)	(2.6484)	(1.6982)	(3.1749)	(1.6433)	(3.7919)
Acquirer and Target Controls	Y	Y	Y	Y	Y	Y
Deal Characteristics	Y	Y	Y	Y	Y	Y
Deal FE	Y	Y	Y	Y	Y	Y
Observations	864	864	864	864	864	864
Adj. R^2	0.0149	0.0156	0.0064	0.0122	0.0033	0.0147

Table A1: Variables, Definitions, and Sources

Variable	Definition	Source
Compustat sample		
MnA	Dummy variable equal to one if a firm becomes a bidder within the year.	SDC
MnA_{target}	Dummy variable equal to one if a firm becomes a target within the year.	SDC
K	Model-implied quantity of AI capital, measured in millions.	Authors' Estimations
Q	Model-implied price of AI capital.	Authors' Estimations
$ShareAI$	The share of AI-related employees of a firm.	Babina et al. (2024)
$ShareAIPost$	The share of AI-skilled job postings.	Babina et al. (2024)
$ShareDataPost$	The share of Data-skilled job postings.	Babina et al. (2024)
$ShareITPost$	The share of IT-skilled job postings.	Babina et al. (2024)
$TotalEmployees$	The number of employees of the firm.	Compustat
$IntangCapital$	The value of a firm's intangible capital.	Peters and Taylor (2017)
$OrgCapital$	The value of a firm's organizational capital.	Peters and Taylor (2017)
$KnowCapital$	The value of a firm's knowledge capital.	Peters and Taylor (2017)
$PatentCapital$	The value of a firm's patent capital.	Woeppel (2022)
$PPENT$	Net property, plant, and equipment.	Compustat
$OtherAssets$	Total assets - $PPENT$.	Compustat
$Size$	Total market capitalization, measured in billions.	CRSP
ROA	Return on assets = EBITDA / total assets.	Compustat
$Leverage$	(Long debt + short debt) / total assets.	Compustat
$TobinQ$	(Total assets + market cap - value of common stock - deferred taxes) / total assets.	CRSP & Compustat
$SalesGrowth$	$(Sales_{it}$ / $Sales_{i,t-1})$ - 1	Compustat
$ProfitMargin$	EBITDA / sales	Compustat
M/B	Market-to-book ratio = market cap / book equity. Market equity is at the fiscal year-end.	CRSP & Compustat
$Volatility$	Realized volatility over the past fiscal year.	CRSP
$PastReturn$	Realized return over the past fiscal year.	CRSP
$TotalAsset$	Total assets, measured in billions.	Compustat
CoE	Cost of equity measure.	Lee et al. (2021)
CoD	Cost of debt: Total interest expenses / total debts.	Compustat
SDC sample		
CAR	Market-adjusted return of the bidder for the three-day window centered on the announcement date of the current deal.	CRSP & Authors' Estimations
CAR_T	Market-adjusted return of the target for the three-day window centered on the announcement date of the current deal.	CRSP & Authors' Estimations
$Synergy$	The combined bidder and target CAR weighted by market value 2 days before the announcement date.	CRSP & Authors' Estimations
$Premium$	Percentage difference between the offer price and the target price (30 days before the deal announcement date).	SDC
$BHAR$	The buy-and-hold abnormal return of the bidder for the 12 months after the announcement date of the current deal.	CRSP & Authors' Estimations
$Stock$	Dummy = 1 if stock is used as part of the consideration in the acquisition.	SDC
SDC sample: Control variables		
$RelSize$	Deal value divided by the acquirer's pre-acquisition market value.	SDC
$Earnout$	Dummy = 1 if the deal includes an earnout, otherwise 0.	SDC
$Tender$	Dummy = 1 if the deal is a tender offer.	SDC
$FullStock$	Dummy = 1 if the deal is 100% paid by stock.	SDC
$FullCash$	Dummy = 1 if the deal is 100% paid by cash.	SDC
$Private$	Dummy = 1 if the target is a private firm.	SDC

Table Continued

Table **A1**: **Variables, Definitions, and Sources (Continued)**

Variable	Definition	Source
$Subsidiary$	Dummy = 1 if the target is a subsidiary.	SDC
$Diversified$	Dummy = 1 if the acquirer and target have different two-digit SIC codes.	SDC
$Hostile$	Dummy = 1 if the acquirer's attitude is hostile.	SDC
$NBidders$	The number of bidders for the target.	SDC
$Toehold$	The percentage of target shares held by the acquirer six months before the acquisition.	SDC
ROA	Return on assets = EBITDA / total assets.	Compustat
$TobinQ$	(Total assets + market cap - value of common stock - deferred taxes) / total assets.	CRSP & Compustat
$Leverage$	(Long debt + short debt) / total assets.	Compustat
M/B	Market-to-book ratio = market cap / book equity. Market equity is at the fiscal year-end.	CRSP & Compustat
$Runup\%$	Cumulative log return from 365 days to 2 trading days before the announcement.	CRSP
$Size$	Total market capitalization, measured in billions.	CRSP

Table A2: Annual Distribution of the M&A Sample

This table presents the annual distribution of M&A announcements between 1 January 2010 and 31 December 2019. *Public*, *Private*, and *Subsidiary* refer to target public status when the classification is available. $Diversified$, $FullCash$, $FullStock$, $Completed$, $Withdrawn$, $Friendly$, and $Tender$ report the number of deals satisfying the corresponding SDC classifications.

Year	Deals	*Public*	*Private*	*Subsidiary*	$Diversified$	$FullCash$	$FullStock$	$Completed$	$Withdrawn$	$Friendly$	$Tender$
2010	229	51	168	9	96	131	2	216	7	228	14
2011	272	38	217	17	107	153	6	252	5	270	13
2012	259	52	205	2	105	159	4	241	7	258	17
2013	220	42	169	8	89	131	6	201	6	220	13
2014	255	48	198	8	92	140	5	235	8	254	18
2015	243	66	172	4	90	167	7	216	9	243	22
2016	187	48	138	0	77	141	2	166	7	185	15
2017	188	42	145	1	89	137	5	164	5	188	7
2018	209	50	152	4	113	160	9	178	5	208	12
2019	116	27	87	2	54	79	4	95	5	116	5
Total	2178	464	1651	55	912	1398	50	1964	64	2170	136

Table A3: Financing Conditions, AI Capital, and Acquisition Activity

This table examines whether financing conditions moderate the relation between AI capital and firms' acquisition activity using the following specification:

$$MnA_{it} = \beta_0 + \beta_1 K_{i,t-1} + \beta_2 Mecha_{i,t-1} + \beta_3 K_{i,t-1} \times Mecha_{i,t-1} + \beta_4 Controls_{i,t-1} + u_{it}$$

MnA equals one if firm i announces an acquisition as an acquirer in year t. K denotes the model-implied quantity of AI capital. $Mecha$ denotes either the cost of equity (CoE) or the cost of debt (CoD). Higher values of CoE and CoD indicate less favorable financing conditions. A subscript $L1$ denotes a one-year lag, and a superscript SD denotes standardization. Control variables are those in Table 4. Numbers in parentheses are t-statistics based on standard errors clustered by firm. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Y: MnA	(1)	(2)
$Mecha$:	CoE	CoD
K_{L1}^{SD}	0.0359	0.0236***
	(1.3887)	(2.9474)
$Mecha_{L1}^{SD}$	-0.0169***	-0.0056**
	(-2.7956)	(-2.4365)
$K_{L1}^{SD} \times Mecha_{L1}^{SD}$	-0.0123**	-0.0138***
	(-2.1397)	(-2.6674)
Controls	Y	Y
Year FE	Y	Y
Firm FE	Y	Y
NObs	9070	10562
Adj. R^2	0.3046	0.2670

Table A4: AI Capital and Deal-Level Outcomes

This table shows the relation between an acquirer's AI capital and deal-level outcomes using the following OLS or LPM models:

$$Outcome_d = \beta_0 + \beta_1 K_d + \beta_2 Controls_d + u_d$$

where *Outcome* denotes the deal-level outcome for deal d, as indicated by the column headings. K_d denotes the acquirer's AI capital measured before the deal announcement. Industry fixed effects refer to the acquirer's Fama–French 48 industry. A superscript ^{SD} means the variable is standardized. Regressions are estimated using OLS for continuous dependent variables and LPM for binary dependent variables. Controls include a series of deal and acquirer characteristics listed under "Control variables" in Panel B of Table 1. *Stock* denotes whether a deal involves stock payment or not. In each column, the corresponding dependent variable is excluded from the set of controls if it is otherwise included as a control variable. For the *Stock* specification, the payment-method controls *FullStock* and *FullCash* are excluded from the control set. See the variable definitions in Table A1. Numbers in parentheses are t-statistics based on standard errors clustered by firm. ***, **, and * denote the significance levels of 1%, 5%, and 10%, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Y:	*RelSize*	*Premium*	*CAR*	CAR_T	*BHAR*	*Stock*	*Private*
K^{SD}	-0.0348***	-2.4627	-0.2749	2.6189	0.7108	0.0066	-0.0260
	(-2.8165)	(-0.6645)	(-1.6319)	(0.9119)	(0.5146)	(0.4841)	(-1.1833)
Controls	Y	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y	Y
Industry FE	Y	Y	Y	Y	Y	Y	Y
NObs	2178	419	2178	316	1982	2178	2178
Adj. R^2	0.1951	0.0624	0.0352	0.1117	0.0207	0.1659	0.3544

Internet Appendix

This Internet Appendix provides supplementary materials supporting the main analysis in the paper. It contains the derivations of the economic model, additional details on the construction and validation of the AI capital measures, and supplementary empirical results, including robustness checks, alternative specifications, competing explanations, and parameter sensitivity analyses.

IA.1. Proof: The Equality of Average Q and Marginal Q

The goal is to show that the average Q equals the marginal Q, and to derive the final system of equations under our assumptions.

From Hall (2001), Hayashi (1982), and Tambe et al. (2020): under the assumption of a zero-rent economy and by applying Euler's Theorem for homogeneous functions of degree 1:

$$
\begin{aligned}
x\frac{\partial f(x)}{\partial x} = f(x) \Rightarrow K_t\frac{\partial V_t(K_t)}{\partial K_t} &= V_t(K_t) \\
\text{Then, } Q_{\text{average}} &= \frac{V_t}{K_t} \\
&= \frac{1}{K_t}V_t \\
&= \frac{1}{K_t}K_t\frac{\partial V_t(K_t)}{\partial K_t} \\
&= \frac{\partial V_t(K_t)}{\partial K_t} = Q_{\text{marginal}} \\
\Rightarrow Q_{\text{average}} &= Q_{\text{marginal}}
\end{aligned}
$$

IA.2. Proof: the Unique Root of the Model

The goal is to show that the function equating average Q and marginal Q has a unique root (i.e., the function $x(K_t) = Q_{\text{marginal}} - Q_{\text{average}}$ has a unique root). For recursive periods with $K_{t-1} > 0$,

we establish this by showing that $x(K_t)$: 1) is monotonically increasing and 2) crosses zero between $\min\{(1-\delta)K_{t-1}, V_t\}$ and $\max\{(1-\delta)K_{t-1}, V_t\}$.

1): $x(K_t)$ is an increasing function if its first derivative is positive

$$\begin{aligned} x(K_t) &= 1 + \alpha\left[\frac{K_t - (1-\delta)K_{t-1}}{K_{t-1}}\right] - \frac{V_t}{K_t} \\ &= \alpha\left[\frac{K_t - (1-\delta)K_{t-1}}{K_{t-1}}\right] + 1 - \frac{V_t}{K_t} \\ x'(K_t) &= \frac{\alpha}{K_{t-1}} + \frac{V_t}{K_t^2} \end{aligned}$$

Given that $\alpha > 0$, $K_{t-1} > 0$, $K_t > 0$, and $V_t \geq 0$, $x'(K_t) > 0$, $x(K_t)$ is strictly increasing.

2) The function crosses zero in the domain: $\{\min[(1-\delta)K_{t-1},\ V_t],\ \max[(1-\delta)K_{t-1},\ V_t]\}$:

if $(1-\delta)K_{t-1} < V_t : \frac{V_t}{(1-\delta)K_{t-1}} > 1, V_t - (1-\delta)K_{t-1} > 0$

$$\begin{aligned} x((1-\delta)K_{t-1}) &= \alpha\left[\frac{(1-\delta)K_{t-1} - (1-\delta)K_{t-1}}{K_{t-1}}\right] + 1 - \frac{V_t}{(1-\delta)K_{t-1}} \\ &= \alpha\left[\frac{0}{K_{t-1}}\right] + 1 - \frac{V_t}{(1-\delta)K_{t-1}} \\ &= 1 - \frac{V_t}{(1-\delta)K_{t-1}} < 0 \\ x(V_t) &= \alpha\left[\frac{V_t - (1-\delta)K_{t-1}}{K_{t-1}}\right] + 1 - \frac{V_t}{V_t} \\ &= \alpha\left[\frac{V_t - (1-\delta)K_{t-1}}{K_{t-1}}\right] + 0 \\ &= \alpha\left[\frac{V_t - (1-\delta)K_{t-1}}{K_{t-1}}\right] > 0 \end{aligned}$$

if $(1-\delta)K_{t-1} > V_t : \frac{V_t}{(1-\delta)K_{t-1}} < 1, V_t - (1-\delta)K_{t-1} < 0$

$$
\begin{aligned}
x((1-\delta)K_{t-1}) &= \alpha\left[\frac{(1-\delta)K_{t-1}-(1-\delta)K_{t-1}}{K_{t-1}}\right]+1-\frac{V_t}{(1-\delta)K_{t-1}} \\
&= 1-\frac{V_t}{(1-\delta)K_{t-1}} > 0 \\
x(V_t) &= \alpha\left[\frac{V_t-(1-\delta)K_{t-1}}{K_{t-1}}\right]+1-\frac{V_t}{V_t} \\
&= \alpha\left[\frac{V_t-(1-\delta)K_{t-1}}{K_{t-1}}\right] < 0
\end{aligned}
$$

In either case, the monotonically increasing function $x(K_t)$ crosses zero from the low to upper bound of the domain $[\min\{(1-\delta)K_{t-1},\ V_t\}, \max\{(1-\delta)K_{t-1},\ V_t\}]$. Then there is a unique root K_t between $(1-\delta)K_{t-1}$ and V_t.

IA.3. Competing Explanations

We also consider four alternative interpretations or mechanisms underlying the baseline relation: defensive motives, positioning motives, misvaluation, and managerial agency. We find no affirmative evidence supporting these alternative explanations.

IA.3.1. Defensive and Positioning Motives

Gorton et al. (2009) propose a defensive-acquisition motive in which firms facing shock-induced creative destruction try to acquire first in order to avoid being "eaten" by others. This motive should be stronger in industries with a larger presence of small and medium-sized firms and be value-destroying. Gorton et al. (2009) also identify a "positioning" motive, where firms acquire others not to grow independently, but to better position themselves for future acquisition by large firms. Such deals should be more likely to emerge in industries with the presence of large AI firms and be value-creating from the option value of future resale. We find no affirmative evidence supporting either the defensive or positioning motive. Table IA2 shows no significant heterogeneity in the baseline relation

across the industry-composition measures, and Table **A4** shows that the acquirer's AI capital does not lead to significantly negative or positive CAR or $BHAR$.

IA.3.2. Misvaluation Hypothesis

There is a potential misvaluation hypothesis, which posits that acquirers exploit overvalued equity to finance acquisitions. According to Harford (2005), deals motivated by misvaluation should disproportionately involve stock payment, deviating from the even likelihood of cash or stock predicted under shock-driven mergers. We do not find affirmative evidence consistent with the misvaluation channel. Table **A4** shows that AI capital is not significantly associated with the indicator for stock payment.

IA.3.3. Agency Problem

This section examines managerial agency as an alternative explanation for the baseline results. One possible concern is that AI-rich firms possess greater financial or organizational capacity to undertake acquisitions, allowing managers to pursue value-destroying deals for private benefits rather than shareholder value (Bebchuk et al., 2009; Chatterjee et al., 2021; Lawrence et al., 2024). This explanation predicts higher offer premiums and poorer post-deal shareholder outcomes. We find no affirmative evidence consistent with this prediction: Table **A4** shows no statistically significant relation between the acquirer's AI capital and $Premium$, CAR, CAR_T, or $BHAR$.

IA.4. Additional Analyses

IA.4.1. Alternative AI-Related Measures

We compare the baseline quantity measure, K, with two alternative AI-related measures: the share of AI-skilled employees ($ShareAI$), the number of AI-skilled employees ($AIEmp$), and the model-implied shadow price of AI capital (Q).

Table IA4 reports the results. In specifications with controls and industry fixed effects, a one-standard-deviation increase in $ShareAI$, $AIEmp$, and Q is associated with 1.30-, 2.50-, and 1.58-percentage-point increases in acquisition probability, respectively. However, all relations become insignificant once firm fixed effects are included: the coefficients fall to 0.0018 for $ShareAI$, 0.0124 for $AIEmp$, and 0.0054 for Q. Thus, these alternative measures do not reproduce the within-firm predictive relation documented for K in the baseline specification.

IA.4.2. AI Capital and Unconditional Target Likelihood

The matched-pair results in Section 7.1 show that AI-intensive targets are selected by acquirers with greater AI capital. We further examine whether AI capital makes a firm generally more likely to become an acquisition target, irrespective of the characteristics of the acquirer. We estimate:

$$MnA_{target,it} = \beta_0 + \beta_1 AIProxy_{i,t-1} + \beta_2 Controls_{i,t-1} + u_{it}, \tag{8}$$

where $MnA_{target,it}$ equals one if firm i becomes an acquisition target in year t, and $AIProxy_{i,t-1}$ denotes alternatively lagged $ShareAI$, K, or Q. Table IA5 provides little evidence that firms with greater AI intensity are unconditionally more likely to become acquisition targets. In the industry-fixed-effects specifications, none of the three AI-related measures is statistically significant. With firm

fixed effects, $ShareAI$ and Q remain insignificant, while the coefficient on K is positive at 0.0027 and is weakly significant at the 10% level. Thus, the unconditional target-likelihood evidence is limited rather than uniformly absent. This pattern contrasts with the substantially stronger matched-pair evidence in Table 9, where the interaction between acquirer AI capital and target AI intensity is consistently positive. Taken together, the evidence is more consistent with complementarity in acquisition matching than with a general preference for AI-intensive targets.

IA.5. Robustness Checks

IA.5.1. Controlling Firms' Data Assets

Prior research shows that firms' data assets are also associated with acquisition activity (Bi et al., 2026). We therefore examine whether the baseline AI-capital relation is subsumed by measures of firms' data assets. We augment the baseline regressions with $DataFreq$ (a 10-K disclosure-based data asset measure) and $KData$ (a model-implied data capital measure) from Bi et al. (2026).

Table IA3 shows that the coefficient on AI capital remains positive and statistically significant in all specifications. $KData$ is also positively and significantly associated with acquisition activity in the firm-fixed-effects specification, whereas the coefficient on $DataFreq$ becomes statistically insignificant once firm fixed effects are included. Thus, the baseline AI-capital relation is not subsumed by either data-asset measure, although the within-firm evidence is stronger for $KData$ than for $DataFreq$.

IA.5.2. Alternative Specifications of Baseline

Table IA6 examines whether the baseline results are sensitive to influential observations in the firm-size distribution and to a logarithmic transformation of AI capital. All specifications include the baseline controls and year and firm fixed effects.

Columns (1) and (2) exclude firms in the top 10% and 5% of the market-capitalization distribution, respectively. The coefficients on AI capital are 0.0132 and 0.0122 and remain statistically significant. Columns (3) and (4) trim both the top and bottom 10% and 5% of the market-capitalization distribution, respectively. The corresponding coefficients are 0.0137 and 0.0124 and remain statistically significant. Column (5) replaces the standardized level of AI capital with $\log(1 + K_{L1})$. The coefficient is 0.0049 and remains significant at the 5% level.

Taken together, these results indicate that the baseline relation is not driven by extreme observations in the firm-size distribution or by the skewness of the level measure of AI capital.

IA.5.3. High-Dimensional Fixed Effects and Pre-Sample Acquisition History

A potential concern with the baseline estimates is that the relation between AI capital and acquisition activity may reflect time-varying shocks that operate at the industry level. Merger activity is known to cluster within industries, and industry-specific technological, product-market, or financing shocks may simultaneously affect firms' accumulation of AI capital and their propensity to undertake acquisitions. To absorb common industry-level shocks flexibly, we replace the conventional year and industry fixed effects with industry-by-year fixed effects. Column (1) of Table IA7 includes industry-by-year fixed effects and the baseline controls, while Column (2) additionally includes firm fixed effects.

Table IA7 reports the results. The coefficient on K_{L1}^{SD} remains significantly positive in both specifications. With firm fixed effects in Column (2), the coefficient is 0.0225, close to the baseline firm-fixed-effects estimate of 0.0221. Thus, the baseline relation is robust to absorbing common shocks at the industry-by-year level.

We next address the possibility that the results reflect persistent differences in firms' underly-

ing propensity to undertake acquisitions. We construct a pre-sample acquisition-history indicator, $PreMnA_i$, equal to one if firm i undertook at least one acquisition during 2000–2008 and zero otherwise. Because $PreMnA_i$ is time-invariant, its level is absorbed by firm fixed effects. We therefore interact $PreMnA_i$ with a full set of year indicators. These interactions allow firms with pre-sample acquisition experience to exhibit unrestricted year-specific differences in acquisition propensity throughout the sample period. This specification is substantially more flexible than imposing a common differential trend and directly controls for the possibility that historically acquisitive firms follow systematically different acquisition paths during the AI-investment period. Table IA8 reports the results. Across specifications that allow acquisition activity to vary flexibly with firms' pre-sample M&A history, the coefficient on K_{L1}^{SD} remains positive and statistically significant, ranging from 0.0192 to 0.0257, around the baseline firm-fixed-effects estimate of 0.0221. The stability of the estimates indicates that the baseline relation is not explained by differential acquisition dynamics associated with firms' pre-sample acquisition experience.

Taken together, the baseline findings are robust to absorbing industry-specific time-varying shocks and to allowing firms with different pre-sample acquisition histories to follow distinct acquisition paths over time. The estimated relation between AI capital and acquisitiveness therefore does not appear to be driven by common industry merger waves or by persistent differences in firms' historical tendency to engage in acquisitions.

IA.5.4. Robust: Model Parameters

We examine the sensitivity of the model-implied AI-capital measures to alternative values of the adjustment-cost parameter α, the initial capital K_0, and the depreciation parameter δ. The time-series path of K is relatively stable across these alternative parameterizations. Changes in the initial condition converge rapidly, while changes in α and δ primarily generate level differences while

preserving a similar upward time-series pattern. The model-implied price Q is more sensitive to parameter choices than K is.

Figure IA1 presents the average time-series paths of AI capital quantity (K) and price (Q) under alternative parameter values. Panels (a) and (b) vary the adjustment-cost parameter α (1.5, 2.0, 3.0, 6.0, 8.0). Panels (c) and (d) vary the initial AI capital K_0 (0, 40% of $PPENT$, 60% of $PPENT$, 80% of $PPENT$, 100% of $PPENT$). Panels (e) and (f) vary the depreciation rate δ (0, 5%, 10%, 40%, 70%). The resulting paths show substantially greater parameter stability for K than for Q, particularly after the initial years of the sample.

Table IA1: Variance Decomposition of AI-Related Measures

The table reports the incremental adjusted R^2 from projections of the AI-related measures on alternative sets of fixed effects. "FF48" denotes the Fama–French 48-industry classification. Panel A uses the full sample, and Panel B uses the sample with non-missing baseline controls used in Table 4.

Panel A: Full Sample			
	ShareAI	K	Q
Year	2.07%	1.35%	2.93%
FF48	4.76%	5.57%	1.76%
FF48 × Year Extra	0.16%	-1.10%	0.04%
Left to "Firm-level"	**93.01%**	**94.18%**	**95.27%**
Persistent between-firm differences.			
Within industries (Firm FE)	**44.36%**	**61.80%**	19.54%
Variation over time and within firms.			
Within firm (Residual)	48.65%	32.38%	**75.73%**
Panel B: Drop Sample with Missing Controls			
	ShareAI	*K*	*Q*
Year	2.14%	1.43%	2.78%
FF48	4.85%	6.03%	1.96%
FF48 × Year: Extra	0.11%	-1.24%	-0.03%
Left to "Firm-level"	**92.90%**	**93.78%**	**95.29%**
Persistent between-firm differences.			
Within industries (Firm FE)	**58.20%**	**86.27%**	27.40%
Variation over time and within firms.			
Within firm (Residual)	34.70%	7.51%	**67.89%**

Table IA2: Industry Composition and Acquisitions: Defensive and Positioning

This table shows how industry composition of AI capital affects the relation between AI capital and acquisitiveness using the following model:

$$MnA_{it} = \beta_0 + \beta_1 K_{i,t-1} + \beta_2 Pct_{jt} + \beta_3 (K_{i,t-1} \times Pct_{jt}) + \beta_4 Controls_{i,t-1} + u_{it}$$

MnA is a dummy equal to one if a firm i announces an M&A deal as an acquirer in a year t. K denotes the model-implied AI capital. A subscript $_{L1}$ means the variable is lagged for one year. A superscript ^{SD} means the variable is standardized. Following the definition of Gorton et al. (2009), Pct refers to one of $Pct_{<5}$, $Pct_{[5,30]}$, or $Pct_{>30}$, indicating the percentage of firms whose K falls within [0%, 5%), [5%, 30%], and (30%, 100%] of the largest K in that industry-year, respectively. Control variables are those in Table **4**. See the variable definitions in Table **A1**. Numbers in parentheses are t-statistics based on standard errors clustered by firm. ***, **, and * denote the significance levels of 1%, 5%, and 10%, respectively.

Y: MnA	Pct_{jt}:	(1) Small AI Firms	(2) Medium AI Firms	(3) Large AI Firms
K_{L1}^{SD}		0.0242***	0.0238**	0.0238***
		(2.7486)	(2.5516)	(2.5808)
Pct_{jt}^{SD}		0.0051	0.0009	-0.0008
		(0.5529)	(0.1290)	(-0.1271)
$K_{L1}^{SD} \times Pct_{jt}^{SD}$		0.0010	-0.0005	-0.0003
		(0.1325)	(-0.0413)	(-0.0872)
Controls		Y	Y	Y
Year FE		Y	Y	Y
Industry FE		Y	Y	Y
NObs		11333	11333	11333
Adj. R^2		0.0983	0.0983	0.0983

Table IA3: AI Capital and Data Assets

This table shows the relation between AI capital and acquisitiveness after controlling for data assets, using the following linear probability model (LPM):

$$MnA_{it} = \beta_0 + \beta_1 K_{i,t-1} + \beta_2 DataAsset_{i,t-1} + \beta_3 Controls_{i,t-1} + u_{it}$$

MnA is a dummy equal to one if a firm i announces an M&A deal as an acquirer in a year t. K denotes the model-implied AI capital. $DataAsset$ is measured by either $DataFreq$ or $KData$ from Bi et al. (2026). Control variables are those in Table 4. A subscript $L1$ denotes a one-year lag, and a superscript SD denotes standardization. See the variable definitions in Table A1. Numbers in parentheses are t-statistics based on standard errors clustered by firm. ***, **, and * denote the significance levels of 1%, 5%, and 10%, respectively.

Y: MnA	(1)	(2)	(3)	(4)
K_{L1}^{SD}	0.0207**	0.0229**	0.0164**	0.0208***
	(1.9958)	(2.2233)	(2.2658)	(2.9118)
$DataFreq_{L1}^{SD}$	0.0154*		0.0095	
	(1.9201)		(1.1780)	
$KData_{L1}^{SD}$		0.0245***		0.0117*
		(2.6731)		(1.8676)
Controls	Y	Y	Y	Y
Year FE	Y	Y	Y	Y
Industry FE	Y	Y	N	N
Firm FE	N	N	Y	Y
NObs	10715	10828	10715	10828
Adj. R^2	0.1049	0.1040	0.2647	0.2635

Table IA4: Alternative AI-Related Measures and Acquisition Likelihood

This table shows the relation between alternative AI-related measures and acquisitiveness The dependent variable MnA is a dummy equal to one if a firm i announces an M&A deal as an acquirer in a year t. The main independent variable denotes either (1) $ShareAI$, the share of AI-skilled employees, (2) $AIEmp$, the number of AI-skilled employees or (3) Q, the model-implied shadow price of AI capital. A subscript $_{L1}$ means the variable is lagged for one year. A superscript ^{SD} means the variable is standardized. Control variables are those in Table 4. See the variable definitions in Table A1. Numbers in parentheses are t-statistics based on standard errors clustered by firm. ***, **, and * denote the significance levels of 1%, 5%, and 10%, respectively.

Y: MnA	(1)	(2)	(3)	(4)	(5)	(6)
$ShareAI_{L1}^{SD}$	0.0130**	0.0018				
	(2.1151)	(0.2832)				
$AIEmp_{L1}^{SD}$			0.0250**	0.0124		
			(2.4581)	(1.0260)		
Q_{L1}^{SD}					0.0158***	0.0054
					(2.8630)	(1.2678)
Controls	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y
Industry FE	Y	N	Y	N	Y	N
Firm FE	N	Y	N	Y	N	Y
NObs	11349	11349	11349	11349	11349	11349
Adj. R^2	0.0977	0.2622	0.0988	0.3055	0.0980	0.2623

Table IA5: AI-Related Measures and Target Likelihood

This table shows the relation between a firm's AI-related measures and the likelihood of becoming a target in the following year using the following model:

$$MnA_{target,it} = \beta_0 + \beta_1 AIProxy_{i,t-1} + \beta_2 Controls_{i,t-1} + u_{it}$$

where $MnA_{target,it}$ is a dummy equal to one if firm i is announced as an acquisition target in year t. $AIProxy$ denotes alternatively $ShareAI$, K, or Q. A superscript SD indicates standardization. Control variables are those in Table 4. See the variable definitions in Table A1. Numbers in parentheses are t-statistics based on standard errors clustered by firm. ***, **, and * denote the significance levels of 1%, 5%, and 10%, respectively.

Y: MnA_{Target}	(1)	(2)	(3)	(4)	(5)	(6)
X:	$ShareAI_{L1}$	K_{L1}	Q_{L1}	$ShareAI_{L1}$	K_{L1}	Q_{L1}
X^{SD}	0.0005	0.0001	0.0000	-0.0000	0.0027*	-0.0000
	(0.6078)	(0.1201)	(0.0329)	(-0.0286)	(1.8384)	(-0.0345)
Controls	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y
Industry FE	Y	Y	Y	N	N	N
Firm FE	N	N	N	Y	Y	Y
NObs	15509	11350	11350	15509	11350	11350
Adj. R^2	0.0008	0.0008	0.0008	0.1036	0.0664	0.0663

Table IA6: Robustness to Firm-Size Restrictions and Alternative Functional Forms

This table reports robustness tests of the relation between AI capital and the likelihood of becoming an acquirer using the following model: The dependent variable is MnA, which equals one if firm i announces an acquisition in year t. The main independent variable K denotes model-implied AI capital. A subscript $_{L1}$ indicates a one-year lag and a superscript ^{SD} indicates standardization. All continuous AI-capital measures, excluding $\log(1+K)$, are standardized before estimation. Robustness tests are alternative firm-size restrictions, including excluding the largest firms and trimming both tails of the firm-size distribution, and $\log(1+K)$. Columns (1)–(2) sequentially exclude firms in the top 10% and 5% of the market-capitalization distribution. Columns (3)–(4) trim both the top and bottom 10% and 5% of the market-capitalization distribution. Column (5) replaces the standardized level of AI capital with $\log(1+K_{L1})$. All specifications include the baseline controls and year and firm fixed effects. See the variable definitions in Table A1. Control variables are those in Table 4. Numbers in parentheses are t-statistics based on standard errors clustered by firm. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Y: MnA	(1)	(2)	(3)	(4)	(5)
Specification:	No Top 10%	No Top 5%	Trim 10% Tails	Trim 5% Tails	$\log(1+K_{L1})$
K_{L1}^{SD}	0.0132***	0.0122***	0.0137***	0.0124***	0.0049**
	(4.9775)	(4.0157)	(4.9231)	(4.0349)	(2.1644)
Controls	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y
Firm FE	Y	Y	Y	Y	Y
NObs	10399	10936	9815	10698	11350
Adj. R^2	0.2335	0.2426	0.2284	0.2393	0.2623

Table IA7: Robustness to Year × Industry Fixed Effects

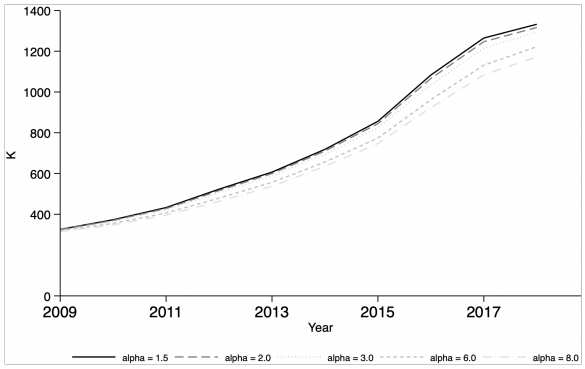
This table reports the baseline relation between AI capital and the likelihood of becoming an acquirer using high-dimensional fixed-effect models. Column (1) includes year × industry fixed effects. Column (2) further includes firm fixed effects. MnA equals one if firm i announces an acquisition in year t. K denotes model-implied AI capital. A subscript $L1$ indicates a one-year lag, and a superscript SD indicates standardization. See the variable definitions in Table A1. Control variables are those in Table 4. Numbers in parentheses are t-statistics based on standard errors clustered by firm. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Y: MnA	(1)	(2)
K_{L1}^{SD}	0.0244**	0.0225***
	(2.4594)	(3.2967)
Controls	Y	Y
Year × Industry FE	Y	Y
Firm FE	N	Y
NObs	11350	11350
Adj. R^2	0.0952	0.2662

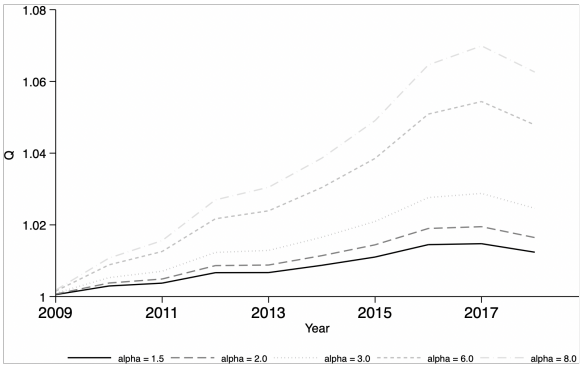
Table IA8: Robustness to Controlling for Pre-Sample M&A History

This table reports the baseline relation between AI capital and the likelihood of becoming an acquirer after controlling for the pre-sample M&A history. All specifications additionally interact $PreMnA_i$ with a full set of year indicators, where $PreMnA_i$ equals one if firm i undertook at least one acquisition during 2000–2008 and zero otherwise. MnA equals one if firm i announces an acquisition in year t. K denotes model-implied AI capital. A superscript ^{SD} indicates standardization. Columns (1) and (2) include conventional year fixed effects, while Columns (3) and (4) replace them with year × industry fixed effects. Columns (2) and (4) further include firm fixed effects. See the variable definitions in Table A1. Control variables are those in Table 4. Numbers in parentheses are t-statistics based on standard errors clustered by firm. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

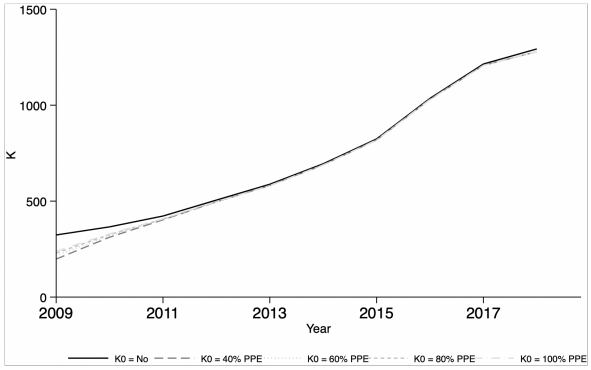
Y: MnA	(1)	(2)	(3)	(4)
K_{L1}^{SD}	0.0249***	0.0192***	0.0257***	0.0196***
	(2.8603)	(3.1633)	(2.8698)	(3.1186)
M&A History × Year FE	Y	Y	Y	Y
Controls	Y	Y	Y	Y
Year FE	Y	Y	N	N
Industry FE	Y	N	N	N
Firm FE	N	Y	N	Y
Year × Industry FE	N	N	Y	Y
NObs	11350	11350	11350	11350
Adj. R^2	0.1411	0.2729	0.1393	0.2773



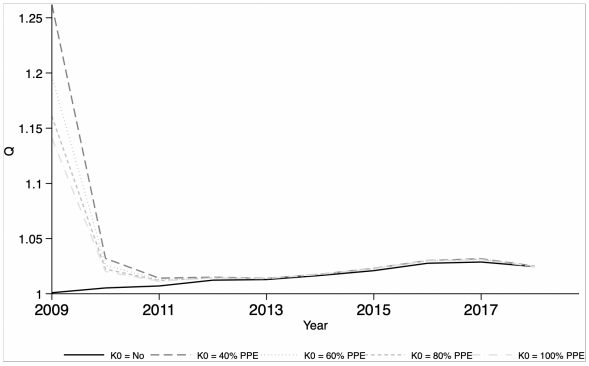
(a) K by Adjustment Costs (α)



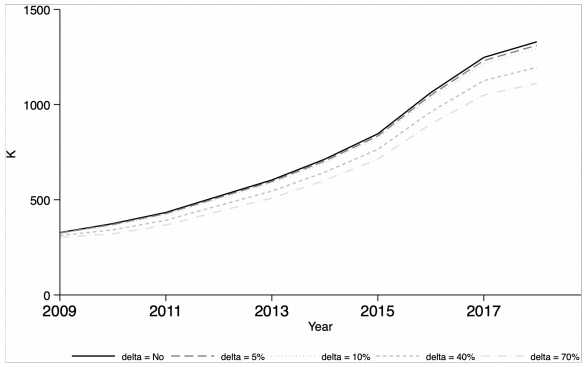
(b) Q by Adjustment Costs (α)



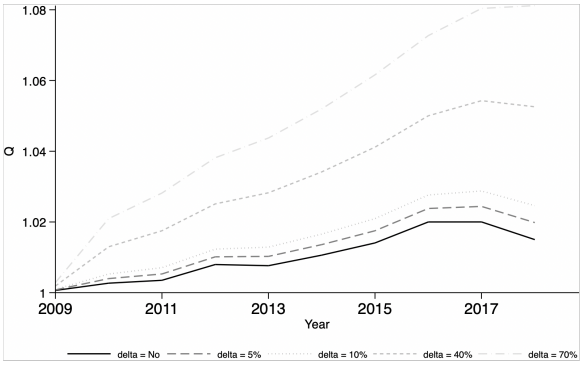
(c) K by Firms' Initial AI Capital Level (K_0)



(d) Q by Firms' Initial AI Capital Level (K_0)



(e) K by Depreciation Rate (δ)



(f) Q by Depreciation Rate (δ)

Figure IA1: Parameter Sensitivity: Time-Series Paths of K and Q under Alternative Model Parameters. This figure plots the average time-series paths of the model-implied quantity (K) and price (Q) of AI capital under alternative parameter values. Panels (a), (c), and (e) plot K, and Panels (b), (d), and (f) plot Q. Panels (a) and (b) vary the adjustment-cost parameter α (1.5, 2.0, 3.0, 6.0, 8.0). Panels (c) and (d) vary initial AI capital K_0 (0, 40% of PPENT, 60% of PPENT, 80% of PPENT, 100% of PPENT). Panels (e) and (f) vary the depreciation rate δ (0, 5%, 10%, 40%, 70%).