

Artificial Intelligence as Relational Capital: Evidence from Major Customer Relationships

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Abstract

This paper examines whether supplier investment in artificial intelligence (AI) broadens firms' customer base or deepens economically important major-customer relationships. Using supplier–customer–year panel data from 2010 to 2021, we find that suppliers with greater AI investment generate higher sales within disclosed major-customer relationships, but are not significantly associated with sales to non-major customers, the addition of newly disclosed major customers, or the number of disclosed major customers. The effect is robust to alternative measures and identification strategies. The effect is stronger when customer-specific knowledge, relationship continuity, and coordination challenges are more important. Further evidence shows that AI-intensive suppliers develop stronger technological linkages with major customers, reflected in supplier citations of customer patents and bilateral patent cross-citations. Finally, AI investment is associated with lower relationship termination and stronger supplier–customer co-movement in stock returns and earnings. Overall, the findings suggest that AI helps suppliers convert customer-specific information into deeper and more durable major-customer relationships rather than broadly expanding the customer base.

Keywords: Artificial intelligence, AI-skilled human capital, Supplier–customer relationships, Major customers, Relationship-specific investments

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1. Introduction

Artificial intelligence (AI) has become an increasingly important technological input into firms' growth and product-market strategies. By improving prediction and learning from large-scale data, AI can help firms make better decisions under uncertainty and identify new opportunities for innovation and growth (Aghion et al., 2017; Agrawal et al., 2019; Furman & Seamans, 2019). Recent evidence shows that AI investment is associated with higher firm growth, product innovation, productivity, and organizational change (Acemoglu et al., 2022; Babina et al., 2024; Czarnitzki et al., 2023; Yang, 2022). However, existing evidence largely focuses on aggregate firm-level outcomes, leaving open how AI-enabled gains are allocated across firms' product-market relationships. Do AI investments help firms broaden their customer base, or do they primarily deepen economically important customer relationships? We examine this question in the context of supplier–major customer relationships and ask whether supplier AI investment increases sales within disclosed major-customer relationships or instead reflects broader customer-market expansion.

Major-customer relationships provide a particularly informative setting for this inquiry because they are economically significant, strategically valuable, and fragile. A small number of large clients often account for a substantial share of supplier revenues. For example, Conagra Brands reports that its largest customer, Walmart, accounted for approximately 29% of consolidated net sales in fiscal 2025.¹ These relationships offer suppliers revenue stability, operational scale, and reputational benefits (Kalwani & Narayandas, 1995; Patatoukas, 2012). Yet they also expose suppliers to customer concentration risk, bargaining pressure, and customer-specific shocks (Cen et al., 2017; Patatoukas, 2012). Given their economic importance, major-customer relationships create strong incentives for suppliers to preserve and expand these ties, shaping important corporate policies and organizational choices, including

¹ See details at: https://www.conagrabrands.com/files/2025-annual-report?utm_source=chatgpt.com.

tax behavior, disclosure practices, and governance structures (Cen et al., 2017; Chen et al., 2022; Minnick & Raman, 2017). These studies highlight suppliers' strategic dependence on major customers, but they provide limited evidence on whether suppliers can strengthen these relationships by improving their ability to understand and respond to customer-specific needs.

Customer-specific learning and adaptation are central to maintaining and deepening major-customer relationships. Suppliers must understand evolving customer needs, anticipate demand changes, adapt products and processes, and coordinate internal activities (Cen et al., 2017; Patatoukas, 2012). AI is particularly relevant to these demands because it enables firms to learn from large volumes of data, improve prediction, and make more informed decisions under uncertainty (Agrawal et al., 2019). These capabilities can improve suppliers' responsiveness to customer-specific needs and help identify product or process improvements that are valuable to major customers. The benefits should be especially valuable in established major-customer relationships, where suppliers have accumulated customer-specific knowledge and coordination routines. In such relationships, AI can help suppliers convert existing relational knowledge into improved customization, adaptation, and execution, thereby increasing relationship-specific sales. We therefore expect supplier AI investment to increase sales to incumbent major customers.

To test our conjecture, we construct a panel of supplier–customer–year observations using data from the Compustat Segment Files, which identify major customers disclosed by suppliers, typically those accounting for at least 10% of a supplier's annual sales. We measure supplier AI investment using the share of employees with AI-related skills, based on a resume-based measure developed by Babina et al. (2024). Our sample covers U.S. public firms from 2010 to 2021, a period during which commercial AI adoption expanded substantially. Our main specification relates supplier AI investment to sales to a given major customer, scaled by supplier sales or assets, and includes supplier-customer pair fixed effects and year fixed effects.

This specification therefore compares changes in sales within the same supplier–customer relationship as supplier AI investment changes over time. We find that suppliers with greater AI investment generate significantly higher sales to existing major customers. Economically, a one–standard-deviation increase in AI intensity is associated with a 12% increase in major customer sales relative to the sample mean. The result is robust to alternative treatments of missing customer sales, alternative major customer sales measures, alternative AI measures, and change specifications that account for the gradual nature of AI investment.

We then distinguish this incumbent-relationship effect from broader customer-market expansion. Prior evidence shows that AI investment is associated with firm growth, product innovation, and expanded offerings (Babina et al., 2024), raising the possibility that AI may help suppliers broaden their customer markets. If so, supplier AI investment should also be associated with sales to non-major customers, the addition of new major customers, or a larger number of disclosed major customers. The evidence does not support this interpretation. Supplier AI investment is not significantly associated with any of these outcomes. These results indicate that the AI-related increase in major-customer sales is concentrated in incumbent relationships rather than broadening the supplier’s customer base.

A key empirical concern is that the relation between supplier AI investment and major-customer sales may reflect omitted variables or reverse causality. To address these concerns, we implement an instrumental variable (IV) strategy that based on firms’ historical hiring links to AI-strong universities, following Babina et al. (2024). This instrument captures variation in firms’ exposure to AI-related human capital that is plausibly exogenous to later customer outcomes. The IV results remain consistent with the baseline estimates, supporting the interpretation that AI investment helps suppliers expand sales to major customers. We also use entropy balancing to reweight non-AI-adopting supplier-year observations so that they resemble AI-adopting supplier-year observations on observable supplier characteristics. The

results remain robust, mitigating concerns that the baseline relation reflects observable differences between AI-adopting and non-adopting suppliers rather than AI investment itself.

We next provide evidence on the technological linkages underlying this relationship-specific deepening. We find that supplier AI investment is positively associated with supplier citations of customer patents and bilateral patent cross-citations between suppliers and incumbent major customers. These findings are consistent with AI helping suppliers apply customer-specific knowledge to product and process adaptation, thereby strengthening established major-customer relationships.

To further assess the relationship-specific adaptation interpretation, we examine whether the effect of supplier AI investment varies with the importance of customer-specific knowledge and coordination. The cross-sectional evidence is consistent with this interpretation. First, the effect is stronger in relationships characterized by greater embeddedness, dependence, or switching frictions, including longer-duration supplier–customer relationships, where repeated interaction allows suppliers to accumulate customer-specific knowledge, suppliers with larger market shares, where incumbent suppliers are more difficult to replace, and suppliers with greater customer concentration, where the payoff to focusing AI-enabled learning and adaptation on a smaller set of economically important customers is higher. Second, the effect is amplified when information-processing and adaptation demands are greater, including in settings with greater supplier organizational complexity, higher customer sales-growth volatility, and cross-industry supplier–customer relationships. These patterns are consistent with AI helping suppliers process information, forecast customer needs, and coordinate customer-specific adaptation. Overall, the cross-sectional results suggest that AI matters most when suppliers can apply it to relationships where customer-specific knowledge, relationship continuity, and operational coordination are central to generating additional sales to major customers.

Finally, we examine relationship-level outcomes that capture the durability and economic alignment of supplier–customer ties. Following prior work that uses relationship termination to study the durability of customer–supplier relationships (Bauer et al., 2018), we find that supplier AI investment is associated with a lower probability that an existing major-customer relationship terminates in the following year. Because customer–supplier relationships transmit value-relevant information across linked firms (Cen & Dasgupta, 2021; Patatoukas, 2012), we also examine co-movement in supplier–customer stock returns and earnings. We find that supplier AI investment is associated with stronger co-movement in both outcomes. Together, these findings indicate that AI-intensive suppliers not only generate higher sales to major customers, but also maintain more durable and economically integrated relationships with those customers over time.

This paper contributes to the growing literature on the economic consequences of AI adoption by identifying a new external, relationship-level function of AI. Prior research primarily studies AI as a productivity-enhancing or innovation-enabling technology that affects firm-level outcomes, including growth, product innovation, labor transformation, risk, governance, and corporate investment policy (Babina et al., 2024; Gounopoulos et al., 2023; Hudson & Morgan, 2024; Webb, 2019; Zhang et al., 2025). Related work also shows that AI can improve information-intensive professional processes, such as audit quality and audit efficiency (Fedyk et al., 2022). However, this literature provides limited evidence on how AI-enabled gains are allocated across firms’ customer relationships. We complement this literature by highlighting major customers as a central but largely overlooked stakeholder in the AI literature. We show that AI-enabled product-market gains are concentrated within existing major-customer relationships rather than being spread broadly across the customer base. Our evidence shows that AI-enabled product-market gains are concentrated within incumbent major-customer relationships rather than being spread broadly across the customer base. This

finding shifts attention from aggregate firm-level growth to the relationship-level allocation of AI-enabled gains. It also suggests that AI helps suppliers convert customer-specific information into stronger sales, technological linkages, and relationship continuity with key customers.

Second, we contribute to the finance literature on customer–supplier relationships by identifying AI as a novel strategic capability that supports relationship-specific adaptation. Prior research shows that major-customer relationships involve relationship-specific investments, incomplete contracting, knowledge sharing, and switching frictions (Cen & Dasgupta, 2021; Minnick & Raman, 2017; Raman & Shahrur, 2008). This literature also documents that suppliers adjust policies, disclosures, governance, and financial decisions in response to important customers (Cen et al., 2017; Chen et al., 2022; Minnick & Raman, 2017). We add to this literature by showing that AI strengthens major-customer relationships along multiple relationship-level dimensions. AI-intensive suppliers develop stronger patent-based technological linkages with major customers, generate larger sales gains when relationships are more embedded and coordination-intensive, experience lower relationship termination, and exhibit stronger economic integration with key customers. These findings suggest that digital capabilities can help suppliers sustain and deepen economically important interfirm ties, especially when customer-specific knowledge and coordination are central to relationship value.

The remainder of the paper proceeds as follows. Section 2 reviews related literature and develops the hypothesis. Section 3 describes the data, variables, and empirical design. Section 4 presents the main results, distinguishes incumbent relationship deepening from broader customer-base expansion, and addresses robustness and identification. Section 5 examines relationship-specific channels. Section 6 studies relationship-level outcomes. Section 7 concludes.

2. Literature Review and Hypothesis Development

2.1. AI Adoption, Firm Growth, and Product-Market Strategy

Recent research increasingly examines AI as a data-intensive technology with broad implications for firm behavior and competitive strategy. Compared with earlier waves of automation that primarily codified routine tasks, AI is distinguished by its ability to learn from large volumes of structured and unstructured data, generate predictions, identify patterns, and support adaptive decision-making (Agrawal et al., 2019; Cockburn et al., 2018). A key feature of AI is that its value depends on the availability and quality of relevant data. Its benefits are therefore likely to be greater when users possess rich, repeated, and decision-relevant information about the task or relationship to which AI is applied. These features make AI particularly useful in settings where firms must learn from dispersed information, forecast uncertain outcomes, and update decisions as new information becomes available.

Building on this view, a growing empirical literature documents that AI adoption affects firm growth, innovation, productivity, and organizational outcomes. Babina et al. (2024) develop a firm-level AI investment measure based on the share of employees with AI-related skills in resume data and show that firms with greater AI investment experience faster sales growth, employment growth, and market valuation growth. They further show that these gains are closely linked to product innovation and product expansion, as AI-investing firms generate more trademarks and product patents, introduce new products, and expand their product portfolios. Related evidence shows that AI-related inventions and AI adoption are associated with higher revenues, productivity, and firm performance (Alderucci et al., 2020; Czarnitzki et al., 2023). At the task level, Brynjolfsson et al. (2025) show that access to generative AI increases productivity among customer-support agents.

Other studies highlight AI's information-processing role in settings such as auditing, corporate information environments, and governance-related decision-making. In auditing,

Fedyk et al. (2022) show that AI investment is associated with improvements in audit quality and audit efficiency, consistent with AI enhancing data-intensive judgment and verification processes. In governance and risk settings, Zhang et al. (2025) show that AI innovation may also improve corporate information environments by strengthening internal controls, increasing information transparency, and reducing information asymmetry, thereby lowering stock price crash risk. Hudson and Morgan (2024) find that firms facing greater AI-related strategic uncertainty benefit from more heterogeneous board networks, suggesting that external knowledge and advice are valuable when firms respond to AI-driven technological change.

Taken together, prior research establishes AI as an important technology for firm growth, innovation, productivity, and information-intensive decision-making. However, this literature has largely examined AI at the firm level, leaving limited evidence on whether AI affects the distribution of economic activity across firms' product-market relationships. Whether AI-enabled product-market gains are concentrated in specific trading relationships, rather than captured only by aggregate firm-level outcomes, remains unexplored in the literature.

2.2. Major-Customer Relationships and Relationship-Specific Investment

Customer–supplier relationships are central to firms' product-market activity, particularly when a small number of major customers account for a substantial share of supplier sales. Major customers may provide more predictable demand, operational scale, information sharing, production coordination, and reputational certification (Cen & Dasgupta, 2021; Kalwani & Narayandas, 1995; Patatoukas, 2012). These benefits make major-customer relationships valuable channels through which suppliers achieve visibility, scale economies, and closer coordination with downstream buyers.

However, dependence on a small number of principal customers also exposes suppliers to concentrated relationship risk. Major customers may exercise bargaining power by

demanding price concessions, delivery flexibility, or other nonprice terms, while undiversified demand makes suppliers more vulnerable to customer-specific shocks. These shocks may originate from disruptions to customer relationships, including takeover threats and customer leadership changes (Cen et al., 2016; Intintoli et al., 2017), supplier-side risk disclosures, such as litigation risk and tax uncertainty disclosure (Cen et al., 2018; Tao et al., 2024), or financial shocks transmitted along the supply chain through distress, bankruptcy, and customer financing conditions (Kolay et al., 2016; Lian, 2024). Given their economic importance, major customers are not merely downstream buyers but key stakeholders that shape supplier operating performance, financing decisions, disclosure choices, investment behavior, and risk exposure.

Because these relationships are valuable but fragile, suppliers often make relationship-specific investments to preserve and deepen them. Transaction-cost economics and property-rights theories emphasize that investments tailored to a specific trading partner are difficult to protect under incomplete contracts because future contingencies, product requirements, and innovation outcomes cannot be fully specified *ex ante* (Klein et al., 1978; Williamson, 1979). In supplier–customer settings, such investments may include customized production processes, technical knowledge, and customer-specific innovation. These investments can create substantial value within the relationship, but they also expose the investing party to opportunism, hold-up, and underinvestment concerns (Minnick & Raman, 2017; Raman & Shahrur, 2008).

Firms use a range of mechanisms to support valuable customer–supplier relationships and mitigate contracting frictions. Prior research shows that these relationships shape suppliers’ reporting, disclosure, and tax decisions because managers internalize the value and risks of major-customer ties. For example, relationship-specific investments influence earnings management incentives when future relationship value depends on perceived supplier and customer performance (Raman & Shahrur, 2008). Suppliers also adjust disclosure choices in

response to customer-related proprietary costs (Chen et al., 2022), and interdependent firms coordinate tax planning decisions in response to supply-chain incentives (Cen et al., 2017). Other studies highlight governance and relational mechanisms that help sustain these ties. Supplier or customer board representation can reduce information risk, strengthen informal relational contracts, and alleviate underinvestment in relationship-specific assets (Minnick & Raman, 2017). Social connections and local social capital can further reinforce trust, support relationship-specific investment, and lengthen supply-chain relationships (Jandik & Salikhova, 2023; Kang et al., 2024). Together, this evidence suggests that major-customer relationships are not passive sales links; they require deliberate disclosure, tax, governance, and relational mechanisms to preserve relationship value.

Knowledge sharing is another important component of relationship-specific investment. In major-customer relationships, suppliers often need to understand customers' technologies, product requirements, production processes, and evolving demand conditions in order to provide customized inputs, improve technical compatibility, and respond to changing customer needs. These knowledge flows can create relationship-specific value because they allow suppliers to adapt products and processes in ways that are more valuable to existing customers than to arm's-length buyers. At the same time, such knowledge is often customer-specific and accumulated through repeated interaction, making it difficult to redeploy fully outside the relationship. Consistent with this view, prior research uses patent citations to trace technological linkages between trading partners and provides evidence of knowledge sharing and relationship-specific innovation between suppliers and customers (Cen & Dasgupta, 2021; Minnick & Raman, 2017). This evidence suggests that major-customer relationships involve not only repeated sales, but also technological learning, customer-specific adaptation, and joint value creation. It also raises the question of whether suppliers' information-processing

capabilities help them convert customer-specific knowledge into deeper incumbent relationships, rather than simply expanding sales across a broader customer base.

2.3. AI-Enabled Customer-Specific Learning and Adaptation

AI may be particularly relevant to major-customer relationships because it improves prediction in settings where firms must learn from large-scale, customer-specific data. By accelerating the accumulation and recombination of knowledge, AI helps firms extract more useful signals from complex information environments (Agrawal et al., 2019; Cockburn et al., 2018). It can also reduce information-processing constraints by improving predictive information for complex business decisions, including customer demand and supply-chain decisions (Krupa & Mullaney, 2026). Major-customer relationships require suppliers to understand evolving customer needs, anticipate demand changes, adjust production processes, and coordinate production activities (Cen & Dasgupta, 2021; Patatoukas, 2012). This task is challenging because demand learning often unfolds gradually as firms learn about customer demand over time through repeated market interactions, rather than observing it perfectly ex ante (Foster et al., 2016). They are also difficult to govern fully through formal contracts because customer needs evolve, relevant contingencies are hard to specify ex ante, and the value of adaptation often depends on accumulated relationship-specific knowledge (Grossman & Hart, 1986; Hart & Moore, 1990; Klein et al., 1978; Williamson, 1985). In this setting, AI can help suppliers extract signals from repeated orders, technical specifications, delivery histories, service requests, and performance feedback, allowing them to identify customer-relevant needs, allocate resources more effectively, and respond more reliably to changing requirements.

AI can support customer-specific adaptation through both execution and innovation. On the execution side, AI functions as a prediction technology that improves decision-making when firms face complex and uncertain information environments (Agrawal et al., 2019; Cockburn et al., 2018; Farboodi & Veldkamp, 2021). This capability is valuable in major-

customer relationships because suppliers must make timely operational decisions based on evolving customer demand, technical requirements, and service feedback (Braguinsky et al., 2021). AI can therefore help suppliers translate customer-specific information into more accurate production schedules, better resource allocation, faster responses to service issues, and more reliable delivery performance. On the innovation side, AI helps firms learn from data, identify patterns, and discover commercially relevant opportunities (Babina et al., 2024). This capability is valuable because major-customer relationships often involve accumulated customer-specific knowledge, technological linkages, and relationship-specific innovation (Cen & Dasgupta, 2021; Minnick & Raman, 2017), and AI may therefore help suppliers convert accumulated customer-specific knowledge into more effective execution and more customer-relevant innovation, thereby strengthening their relationships with customers.

These capabilities should be particularly useful in incumbent major-customer relationships, where suppliers have already accumulated customer-specific knowledge through repeated interaction. Because AI systems depend on relevant data to generate useful predictions and recommendations, incumbent relationships provide a particularly valuable information base. Major customers generate repeated transactions, technical specifications, delivery histories, service feedback, and knowledge about changing customer needs. When suppliers invest in AI, this stock of relationship-specific information becomes more actionable, allowing suppliers to tailor products and processes, improve coordination, and respond more effectively to established customers. This logic implies that AI-enabled learning and innovation should translate disproportionately into additional sales within incumbent major-customer ties. Although AI may also support broad product-market growth by enabling new products or expanded offerings, such broad expansion is less directly tied to the accumulated customer-specific information and coordination routines embedded in existing major-customer

relationships. Accordingly, suppliers with greater AI investment should be better positioned to increase sales within major-customer relationships. We therefore state the following hypothesis:

Hypothesis 1 (H1): *Supplier AI investment is positively associated with sales to major customers.*

3. Data and Empirical Strategy

3.1 Data and Sample Construction

We construct our sample of supplier–customer relationships from Compustat’s Segment Customer files, which report the identity and sales share of major customers. U.S. public firms are required under SEC Regulation S-K and SFAS 131 to disclose the identity and sales amount of any customer that accounts for 10% or more of consolidated revenues. In practice, however, firms often also voluntarily disclose smaller customers that they regard as strategically important. Following prior work, including Chen et al. (2021) and Intintoli et al. (2017), we include all disclosed customers in our analyses. Our sample period spans 2010–2021, consistent with Babina et al. (2024), who show that the commercial adoption of AI technologies accelerated beginning in 2010. We exclude utilities (SIC 4900–4999), financial firms (SIC 6000–6999), and cases in which one party is a subsidiary of the other.

Because customer names in the Compustat Segment files are not directly linked to Compustat firm identifiers, we follow Minnick and Raman (2017) to match disclosed customer names to firms in Compustat Fundamentals. We first standardize customer names by removing legal suffixes, punctuation, and common abbreviations. We then apply fuzzy string matching between the standardized customer names and Compustat firm names. Ambiguous matches are manually verified using additional identifiers, including tickers, CIKs, and CUSIPs, and uncertain matches are excluded to minimize customer misclassification.

To construct the supplier–customer–year panel and capture gradual deterioration rather than abrupt termination, we follow the convention in the customer–supplier literature and adopt

the approach of Intintoli et al. (2017). Specifically, we extend the panel for three fiscal years after the last reported sale and assign customer sales of zero in those years.² Similarly, we also assign customer sales of zero to any missing years between the first and last customer disclosure, thereby maintaining a continuous relationship period.

We merge the supplier–customer panel with Compustat Fundamentals for financial variables, CRSP for stock returns, and LSEG (13F) for institutional ownership. Our final sample comprises 3,902 supplier–customer–year observations with non-missing values for our key variables, representing 691 unique suppliers and 490 unique customers over the 2010–2021 period.

3.2 Variable Construction

Our main dependent variables measure the economic significance of a supplier’s relationship with a disclosed major customer. Using the supplier–customer–year structure described above, we follow Chen et al. (2021) and construct two measures of major-customer sales. *MCS-to-Sales* is the natural logarithm of one plus sales to a major customer scaled by the supplier’s total sales. *MCS-to-Assets* is the natural logarithm of one plus sales to a major customer scaled by the supplier’s total assets. These measures capture the relative importance of a given customer relationship to the supplier’s operating scale and asset base.

Our main proxy for firm-level AI investment is the employee-based measure of AI intensity developed by Babina et al. (2024). This measure uses resume data from Cognism to identify workers with AI-related skills (e.g., machine learning, natural language processing, computer vision) and defines *AI Intensity* as the proportion of a firm’s employees classified as AI-skilled. Unlike financial disclosures, which rarely isolate AI-related expenditures, this proxy captures the organizational embedding of AI expertise within the firm. Babina et al. (2024) validate the measure by showing that it correlates strongly with alternative indicators

² We use three years because the median customer–supplier relationship in our sample lasts three years.

such as AI-related patents and purchases of external AI solutions, and that it predicts growth in innovation outputs, trademarks, and product expansion.

This employee-based measure is appropriate for our setting because AI adoption requires specialized human capital that enables firms to develop, implement, and integrate AI tools into business processes. Prior research shows that AI is directed toward data-intensive and high-skilled tasks, including prediction, pattern recognition, and analytical decision-making (Felten et al., 2021; Webb, 2019). Related evidence from audit firms shows that AI-skilled employees are central to AI adoption and that such investments improve quality and efficiency in information-intensive processes (Fedyk et al., 2022). Accordingly, the share of AI-skilled employees captures not only the use of AI technologies, but also the internal capability to apply AI to operational and product-market decisions.

We also include supplier- and customer-level controls commonly used in prior customer–supplier studies. These variables are defined in Appendix Table A1.

3.3 Descriptive Statistics

Table 1 reports descriptive statistics. All continuous variables are winsorized at the 1st and 99th percentiles. Monetary values are adjusted for inflation and expressed in constant 2021 dollars using the Consumer Price Index (CPI).

The mean value of *MCS-to-Sales* and *MCS-to-Assets* are 0.082 and 0.077, respectively, comparable to those reported in Chen et al. (2021). The mean value for *AI Intensity* is 0.094, suggesting that, on average, only 0.094% of employees possess AI-related skills. This value is within the range documented by Babina et al. (2024), consistent with the view that AI-skilled labor remains concentrated among a relatively small share of employees during our sample period.

The distribution of the control variables is also broadly comparable to prior studies on customer–supplier relationships. For example, the mean value of supplier Firm Size is 6.511,

while the mean value of Customer Firm Size is 8.289, consistent with prior evidence that major customers are substantially larger than their dependent suppliers (Cen et al., 2017). The mean values of supplier R&D intensity and capital expenditures are 0.076 and 0.045, respectively, close to the corresponding magnitudes reported in Intintoli et al. (2017). Supplier profitability is also of a similar order of magnitude, with a mean ROA of 0.051.

[Table 1 Around Here]

3.4 Empirical Design

To examine the effect of suppliers' AI investment on sales to major customers, we estimate the following specification:

$$MCS_{ij,t} = \alpha + \beta_1 AI Intensity_{i,t} + \delta X_{ij,t} + \omega_{ij} + \lambda_t + \varepsilon_{ij,t} \quad (1)$$

where $MCS_{ij,t}$ is sales from suppliers i to customer j at time t , measured by *MCS-to-Sales* or *MCS-to-Assets*. $AI Intensity_{i,t}$ is our proxy for supplier i 's AI investment. Our hypothesis predicts a positive β_1 , indicating that greater AI adoption enables suppliers to expand sales to major customers. $X_{ij,t}$ represent a vector of supplier- and customer-level controls identified in Intintoli et al. (2017) as important determinants of supplier–customer sales. Supplier controls include profitability (*ROA*), growth opportunities (*Sales Growth*), natural logarithm of total sales (*Firm Size*), stock return volatility (*Volatility*), natural logarithm of firm age (*Firm Age*), selling expenses (*SG&A*), R&D intensity (*R&D*), capital expenditures (*CAPEX*), book leverage (*Leverage*), a dividend payer indicator (*Dividend*), and a blockholder indicator (*Blockholder*). Customer controls include the natural logarithm of total sales (*Customer Firm Size*), customer profitability (*Customer ROA*), R&D intensity (*Customer R&D*), book leverage (*Customer Leverage*), asset growth (*Customer Asset Growth*), and annual stock return (*Customer Return*).

In addition, we include supplier-customer pair fixed effects (ω_{ij}) to account for time-invariant relationship characteristics such as contracting terms, product compatibility, or

relationship-specific investments, and year fixed effects (λ_t) to absorb aggregate shocks. Standard errors are clustered at the supplier level to account for heteroskedasticity and serial correlation.

4. Empirical Results

4.1 AI Investment and Sales to Major Customers

Table 2 presents the baseline estimates of the relation between supplier AI investment and sales to major customers using Eq. (1). Column (1) reports results using *MCS-to-Sales* as the dependent variable, while Column (2) uses *MCS-to-Assets*. Across both specifications, the coefficient on *AI Intensity* is positive and statistically significant at the 1% level. The estimated coefficients are 0.035 in Column (1) and 0.032 in Column (2), indicating that suppliers with greater AI investment generate higher sales from their major-customer relationships. The effect of AI investment is not only statistically associated with major-customer sales, but also economically relevant for the importance of these relationships to suppliers. A one-standard-deviation increase in *AI Intensity* raises both *MCS-to-Sales* and *MCS-to-Assets* by about 12 percent relative to their sample means.³

[Table 2 Around Here]

The coefficients on the control variables are generally consistent with prior customer–supplier studies. For example, supplier stock return volatility (*Volatility*) and age (*Firm Age*) are negatively related to sales to major customers, consistent with the view that more stable and younger suppliers may be more dependent on key customer relationships (Chen et al., 2021; Intintoli et al., 2017). On the customer side, customer R&D intensity (*Customer R&D*) is positively associated with major-customer sales, consistent with the idea that innovative customers may require greater supplier adaptation and relationship-specific investment.

³ Computed as $0.035 \times 0.282 / 0.082 = 12.0\%$ for *MCS-to-Sales*, and $0.032 \times 0.282 / 0.077 = 11.7\%$ for *MCS-to-Assets*.

Overall, the baseline evidence supports H1. Suppliers with greater AI investment generate higher sales from major customers across both measures of major-customer sales. These findings extend Babina et al. (2024), who show that AI investment is associated with firm growth, by showing that AI-related growth is reflected in suppliers' relationships with economically important customers. The results are also consistent with the customer–supplier literature emphasizing the importance of relationship-specific investments and the resources firms devote to sustaining major-customer ties (Raman and Shahrur, 2008; Minnick and Raman, 2017).

4.2 AI and Broader Customer-Market Expansion

We next examine whether the increase in major-customer sales reflects broader customer-base expansion. Expanding the customer base is economically distinct from deepening existing relationships because forming, managing, and terminating supply-chain relationships involves meaningful adjustment costs (Xu et al., 2023). If AI helps suppliers scale more broadly by commercializing expanded offerings across a wider set of buyers, we should observe increases not only in sales to existing major customers, but also in sales outside the major-customer base, the formation of new major-customer relationships, or the number of disclosed major customers.

Table 3 examines whether supplier AI investment is associated with broader customer-market expansion. We use a supplier-year panel because the dependent variables capture the supplier's overall non-major-customer sales and customer-base structure, rather than sales within a specific supplier–customer pair. Column (1) uses *Non-major Customer Sales* as the dependent variable, which captures supplier sales not attributed to disclosed major customers. Column (2) uses *Add Major Customers*, an indicator equal to one if the supplier adds a new disclosed major customer in a given year, and zero otherwise. Column (3) uses *Number Major*

Customers, which measures the number of disclosed major customers reported by the supplier in a given year.

[Table 3 Around Here]

Across all three outcomes, the coefficients on AI Intensity are statistically insignificant. Thus, these results do not support the interpretation that supplier AI investment operates mainly through broad customer-market expansion. However, the contrast with the positive baseline results is informative. AI investment is associated with higher sales within disclosed major-customer relationships, but not higher sales outside the major-customer base, the formation of newly disclosed major-customer relationships, or a larger disclosed customer portfolio. This pattern helps distinguish relationship-specific deepening from general market expansion and suggests that AI-related gains are realized primarily where suppliers can apply customer-specific information, accumulated transaction histories, and established coordination channels.

4.3 Robustness Tests

4.3.1 Alternative Treatments of Missing Customer Sales

Our baseline analysis follows prior studies by setting customer sales to zero in nondisclosure years between the first and last appearance of a relationship and by extending the panel for three years after the last disclosure (Chen et al., 2021; Intintoli et al., 2017). To ensure that our findings are not sensitive to this treatment, we re-estimate the baseline analysis using alternative treatments of missing customer sales. Table 4 reports the results.

[Table 4 Around Here]

Columns (1) and (2) exclude supplier–customer–year observations with missing customer sales between the first and last disclosure of a relationship. The coefficient on AI Intensity remains positive and statistically significant, consistent with the baseline results, indicating that the relation between supplier AI investment and major-customer sales is not driven by assigning zero sales to within-relationship nondisclosure years.

Next, to test whether the results depend on assuming that a relationship persists for three years after the last reported sale, Columns (3)–(4) and (5)–(6) restrict the post-disclosure extension window to one and two years, respectively, instead of the three-year window used in the baseline specification. Across both alternatives, the coefficients on *AI Intensity* remain positive and statistically significant. This evidence suggests that our main findings are not an artifact of the assumed length of the post-disclosure relationship window.

Finally, Columns (7) and (8) adopt the imputation strategy proposed by Intintoli et al. (2017), assigning missing customer sales a value equal to 10% of supplier revenues rather than zero. This approach considers the possibility that nondisclosure occurs when a customer's sales contribution falls just below the mandatory reporting threshold, but the relationship may persist at a sub-threshold but still economically meaningful level, rather than ending entirely. Under this approach, the estimated coefficients on *AI Intensity* are smaller, consistent with reduced variation in measured customer sales when positive sales are assigned to nondisclosure years. Nevertheless, the coefficients remain positive and statistically significant.

Taken together, these robustness checks confirm that our baseline results are not driven by specific assumptions about missing customer sales or the length of the post-disclosure relationship window. Supplier AI investment remains positively associated with sales to major customers across alternative treatments of nondisclosure years, reinforcing the conclusion that AI investment is linked to stronger sales ties with major customers.

4.3.2 Change Specifications and the Slow-Moving Nature of AI Investment

Given that AI adoption, especially AI-related human capital, accumulates gradually within firms, our main explanatory variable, *AI Intensity*, is relatively slow-moving. This raises the concern that the baseline results may partly reflect persistent cross-sectional differences across suppliers rather than changes in AI investment over time. Consistent with this view, Babina et

al. (2024) emphasize that AI investment is a slow-moving organizational process and use long-difference specifications to capture persistent changes in firm-level AI adoption.

To address this concern, we estimate a three-year long-difference specification that relates changes in AI Intensity from year t to year $t+3$ to contemporaneous changes in major-customer sales over the same period.⁴ This approach focuses on multi-year changes in supplier AI investment and therefore better captures the gradual nature of AI adoption. It also aligns with the idea that AI-enabled improvements in customer-specific learning, coordination, and adaptation are unlikely to translate into major-customer sales immediately, but instead unfold over a multi-year horizon.

Table 5 reports the results. The coefficient on $\Delta AI\ Intensity$ remains positive and statistically significant for both $\Delta MCS\text{-}to\text{-}Sales$ and $\Delta MCS\text{-}to\text{-}Assets$. These findings indicate that suppliers that increase AI investment over multi-year horizons also experience increases in sales to major customers. The results therefore suggest that our baseline evidence is not driven solely by persistent cross-sectional differences across suppliers, but is also present in within-supplier changes over time.⁵

[Table 5 Around Here]

4.3.3 Alternative Measures of Major-Customer Sales and AI Investment

We next assess whether our findings are robust to alternative measures of major-customer sales and supplier AI investment. Table 6 reports the results.

Panel A explores two alternative dependent variables. In Column (1), we replace the scaled major-customer sales measure with the natural logarithm of the level of major-customer sales ($\ln Major\ Customer\ Sales$). The coefficient on $AI\ Intensity$ remains positive and

⁴ Three years also aligns with the median length of supplier–customer relationships in our sample and with the way we extend relationships in sample construction.

⁵ In Table A.2, we further assess robustness by estimating annual first-difference specifications and alternative specifications using three-year moving averages of AI investment and major-customer sales. The results remain consistent with our main findings.

statistically significant (0.598, $p < 0.01$). To capture whether supplier AI investment is associated with the continued reporting of sales to a disclosed major customer, Column (2) uses an indicator, *Positive Major Customer Sales*, equal to one if the supplier reports positive sales to the disclosed customer in a given year, and zero otherwise. The estimated coefficient on AI Intensity is 0.154 ($p < 0.05$), indicating that firms with greater AI adoption are significantly more likely to continue reporting sales to their largest customer.

[Table 6 Around Here]

Panel B uses an alternative measure of supplier AI investment. Following Babina et al. (2024), we use the share of AI-related job postings from Burning Glass, *AI Intensity BG*, as a proxy for firm-level AI engagement. This measure identifies AI-related positions based on detailed skill requirements in job postings and captures firms' demand for AI-skilled labor.⁶ Columns (3) and (4) of Table 6 show that the results remain consistent with the baseline. The coefficients on *AI Intensity BG* remain positive and statistically significant for both MCS-to-Sales and MCS-to-Assets.

Overall, Table 6 shows that the positive relation between supplier AI investment and major-customer sales is robust to alternative measures of both the dependent variable and the main explanatory variable. This evidence reinforces our conclusion that AI investment is associated with stronger sales ties between suppliers and their major customers.

Finally, we conduct additional robustness tests for the customer-base outcomes examined in Section 4.2. Internet Appendix Table IA.3 reports results using alternative constructions of non-major-customer sales, the job-posting-based measure of AI investment, and a change specification for the number of disclosed major customers. Across these tests, supplier AI investment remains statistically insignificant, reinforcing the conclusion that AI-

⁶ Because this dataset ends in 2018 and only covers firms with sufficient online recruitment activity from Burning Glass, the sample size in Panel B is smaller than in the baseline analysis.

related sales gains are concentrated in incumbent major-customer relationships rather than broader customer-base expansion.

4.4 Endogeneity Concerns

Our baseline results show a positive association between supplier AI investment and sales to major customers. Although the specifications include supplier–customer pair fixed effects, year fixed effects, and a rich set of supplier- and customer-level controls, endogeneity concerns may remain. In particular, unobserved strategic changes, technological upgrading, or customer-driven demand for greater customization could increase both a supplier’s AI investment and its sales to major customers. Reverse causality may also arise if suppliers increase AI investment in response to expanding major-customer relationships or the evolving needs of key customers. We address these concerns using two complementary approaches, an instrumental-variable analysis and entropy balancing.

4.4.1 Instrument Variable Approach

We first follow Babina et al. (2024) and implement an instrumental-variable strategy based on firms’ historical exposure to AI-strong universities. The instrument exploits pre-2010 firm–university hiring networks and variation in universities’ AI research intensity before the commercial expansion of AI. The underlying intuition is that firms with stronger historical hiring links to AI-strong universities had greater access to AI-trained human capital when commercial AI adoption accelerated, generating plausibly exogenous variation in their ability to build AI capabilities.

The instrument, *AI-Strong Uni Hiring*, is constructed by aggregating each university’s AI strength by the share of the firm’s 2010 Science, Technology, Engineering, and Mathematics (STEM) employees graduating from that university. This measure captures predetermined access to AI-capable human capital and is less likely to be driven by later supplier–customer outcomes because it is based on historical hiring networks and universities’ pre-commercial AI

research strength. However, because the instrumental variable is time-invariant at the supplier level, we cannot include supplier–customer pair fixed effects in the IV specification. Instead, following Chen et al. (2021), we include supplier fixed effects, customer fixed effects, and year fixed effects. Table 7 reports the results.

[Table 7 Around Here]

Columns (1) and (2) first report OLS estimates using the fixed-effects structure employed in the IV analysis. The coefficients on AI Intensity remain positive and statistically significant, indicating that the baseline relation is not driven by the alternative fixed-effects structure. Column (3) reports the first-stage regression. The coefficient on *AI-Strong Uni Hiring* is positive and statistically significant, confirming the relevance of the instrument. Columns (4) and (5) report the second-stage results. The instrumented values of AI Intensity remain positive and statistically significant for both measures of major-customer sales, supporting a causal interpretation of the relation between supplier AI investment and sales to major customers.

Columns (6) – (10) repeat the analysis by additionally control for *Top-10 Uni Hiring measure*, following Babina et al. (2024). This control captures a firm’s general access to elite educational institutions and helps address the concern that the instrument may proxy for broader talent pipelines, managerial quality, or prestige effects rather than access to AI-specific human capital. Although exposure to top universities is positively associated with both AI investment and major-customer sales, including this control does not alter the positive and statistically significant coefficient on instrumented AI Intensity. This evidence suggests that the IV results are not driven by general exposure to elite talent, but instead reflect access to AI-capable human capital.

Taken together, the IV results support a causal interpretation that supplier AI investment continues to predict higher sales to major customers.

4.4.2 Entropy Balance Technique

We next use entropy balancing to address the concern that suppliers with AI investment may differ systematically from suppliers without AI investment along observable characteristics. Although our baseline specifications control for a rich set of supplier and customer characteristics, suppliers that invest in AI may still differ from non-AI suppliers in ways that affect major-customer sales. Entropy balancing helps mitigate this concern by reweighting the non-AI supplier group so that it closely matches the AI supplier group on the observable supplier characteristics used in the baseline analysis.

Panel A of Table 8 reports the balance diagnostics before and after weighting. Before weighting, suppliers with AI investment differ from suppliers without AI investment across several observable characteristics. However, after applying entropy balancing, the weighted non-AI supplier group closely matches the AI supplier group in the means of the covariates, indicating that the procedure substantially improves covariate balance. Panel B reports the weighted regression results using the entropy-balancing weights. The coefficient on *AI Intensity* remains positive and statistically significant across both specifications. This evidence indicates that the baseline findings are not driven by observable differences between suppliers with and without AI investment.

[Table 8 Around Here]

Overall, the entropy-balancing results provide additional support for our main inference. After improving covariate balance between AI and non-AI suppliers, supplier AI investment remains positively associated with sales to major customers. This evidence reduces the concern that our findings simply reflect observable supplier heterogeneity.

We further apply the IV and entropy-balancing approaches to the customer-base outcomes examined in Section 4.2. Internet Appendix Tables IA.4 and IA.5 report the IV and entropy-balanced estimates, respectively. The results continue to show that supplier AI

investment is not significantly associated with non-major-customer sales, the addition of new major customers, or the number of disclosed major customers.

5. Relationship-Specific Deepening: Mechanism and Cross-Sectional Evidence

The evidence so far indicates that AI-related sales gains are concentrated within major customers rather than broader customer-base expansion, we next examine the mechanisms and conditions underlying this relationship-specific deepening. We argue that AI helps suppliers use accumulated customer-specific information and established coordination routines to learn from, adapt to, and innovate for major customers. We examine this interpretation in two ways. First, we test whether AI investment is associated with stronger customer-specific technological linkages between suppliers and their major customers, using supplier citations of customer patents and bilateral patent cross-citations. Second, we examine whether the AI–major-customer sales relation is stronger in settings where relationship-specific capabilities should be more valuable, including relationships characterized by greater embeddedness, dependence, and coordination complexity. These tests further discipline the interpretation by examining whether the AI effect is amplified in settings where customer-specific learning, adaptation, and coordination should be most valuable.

5.1 Customer-Specific Technological Linkages

Supplier-customer relationships often involve innovation activities whose value is specific to the focal trading relationship. Suppliers may need to understand customers’ technologies, product requirements, and evolving technical needs in order to adapt products, improve compatibility, and support customer-specific innovation. Patent citations between suppliers and customers provide evidence of technological knowledge flows and innovation linkages between supply-chain partners (Cen and Dasgupta, 2021; Minnick and Raman, 2017). Accordingly, if AI helps suppliers process technical information more effectively and tailor

innovation to customer needs, supplier AI investment should be associated with stronger patent-based technological linkages with major customers.

The results in Table 9 are consistent with this prediction. The dependent variable in Column (1) is *Supplier Cites Customer*, which equals one if the supplier's patent cites at least one patent owned by its major customer, and zero otherwise. The coefficient on *AI Intensity* is positive and statistically significant, indicating that AI-intensive suppliers are more likely to build on the technological knowledge of their major customers. Column (2) uses *Cross-Citation* as the dependent variable, which equals one if there is at least one citation between the supplier's and customer's patents in either direction. The coefficient on *AI Intensity* is again positive and significant, suggesting stronger bilateral technological linkages between suppliers and major customers.

[Table 9 Around Here]

Taken together, these results suggest that AI-intensive suppliers are more likely to incorporate major-customer knowledge into their innovation activities and develop stronger technological linkages with those customers. This pattern is consistent with relationship-specific deepening, whereby AI is associated with customer-specific learning, technological adaptation, and innovation within supplier–customer relationships. This evidence also complements Babina et al. (2024), who show that AI-related firm growth is closely linked to product innovation, by showing that AI-enabled innovation is connected to customer-specific knowledge and technological linkages with economically important customers.

5.2. Heterogeneity by Relationship Embeddedness and Coordination Complexity

We next examine whether the AI effect is stronger in settings where relationship-specific learning, adaptation, and coordination should be more valuable. The mechanism implies two related sources of heterogeneity. First, AI should be more valuable when suppliers have richer customer-specific information and stronger economic incentives to deepen key customer

relationships. We capture this dimension using relationship duration, customer concentration, and supplier market share. Second, AI should be more valuable when serving major customers requires greater information processing, adaptation, and coordination. We capture this dimension using supplier complexity, customer demand volatility, and cross-industry supplier–customer relationships. Table 10 reports the results.

[Table 10 Around Here]

5.2.1 Relationship Embeddedness and Economic Incentives

Panel A of Table 10 examines whether the AI effect is stronger when supplier–customer relationships are more embedded or economically important. Suppliers must have customer-specific information that AI can help process, incentives to apply AI toward economically important customers, and sufficient product-market strength to convert improved responsiveness, customization, and coordination into greater relationship-level sales. We therefore examine relationship duration, customer concentration, and supplier market share..

We begin with relationship duration. A longer supplier-customer relationship reflects repeated exchange and accumulated customer knowledge (Chen et al., 2021; Intintoli et al., 2017). Such relationships provide a richer information base for AI-enabled learning because suppliers have more historical experience with the customer’s demand patterns, technical requirements, and operating routines. Consistent with this logic, Columns (1) and (2) show that the interaction between *AI Intensity* and *Long Duration* is positive and statistically significant for both *MCS-to-Sales* and *MCS-to-Assets*. The stronger effect in long-standing relationships suggests that AI investment is more valuable when suppliers can apply it to relationships with accumulated customer-specific knowledge.

We next consider customer concentration. Greater customer concentration implies that a supplier depends more heavily on a limited number of important customers. In such settings, the payoff from using AI to improve customer-specific learning, coordination, and adaptation

is likely to be higher because relationship-level gains account for a larger share of the supplier's overall business. Consistent with this argument, the interaction between *AI Intensity* and *High Customer Concentration* is positive and significant in Columns (3) and (4). This result suggests that AI effect is stronger when suppliers have greater economic incentives to focus on key customer relationships.

Columns (5) and (6) examine supplier market shares. Suppliers with larger market shares are likely to have stronger competitive positions, greater operating scale, and capabilities that are more difficult for customers to replace (Chen et al., 2021; Intintoli et al., 2017). These conditions strengthen the relationship-specific capability channel because AI-enabled improvements in responsiveness, customization, and coordination are more likely to translate into additional purchases when the supplier is a more important or less easily substitutable counterparty. In Columns (3) and (4), the interaction between *AI Intensity* and *Large Market Share* is positive and significant, indicating that the AI effect is amplified when suppliers occupy stronger product-market positions.

Overall, Panel A indicates that the AI effect is stronger when suppliers have accumulated customer-specific information, stronger incentives to deepen key customer relationships, and stronger competitive positions. This evidence supports the relationship-specific capability interpretation by showing that AI creates greater value when suppliers can apply it to commercially important relationships with established knowledge, stronger economic incentives, and higher switching frictions.

5.2.2 Adaptation and Coordination Complexity

Panel B of Table 10 examines whether the AI effect is stronger when major-customer relationships involve greater adaptation and coordination demands. Such relationships require suppliers to convert customer-specific information into operational decisions under greater complexity or uncertainty. Because AI enables firms to learn from large amounts of data,

improve prediction, and tailor offerings to customer needs (Babina et al., 2024), AI investment should be especially valuable when customer-specific adaptation is more difficult.

Columns (1) and (2) examine supplier organizational complexity. Suppliers operating across multiple business segments face greater challenges in coordinating internal resources and adapting products or processes to customer needs. These firms must process information across business lines and allocate resources in ways that meet the requirements of key customers. Consistent with Patatoukas (2012), who emphasizes the importance of information transfer and coordination in major-customer relationships, the interaction between *AI Intensity* and *High Segment Complexity* is positive and statistically significant for both *MCS-to-Sales* and *MCS-to-Assets*.

Columns (3) and (4) focus on customer sales-growth volatility. More volatile customer demand makes it harder for suppliers to forecast customer needs and coordinate production, capacity, and delivery decisions. Because AI can improve forecasting and help firms identify patterns in complex demand environments, its value should be greater when customer-specific planning is more uncertain (Babina et al., 2024). Consistent with this prediction, the interaction between *AI Intensity* and *High Customer Sales Growth Volatility* is positive and statistically significant.

Columns (5) and (6) examine whether the supplier and customer operate in different industries. Cross-industry relationships are likely to involve greater coordination challenges because customer needs must be translated across different technological, organizational, and product-market domains. These relationships may require more specialized inputs, customized processes, and knowledge sharing that are difficult to standardize, consistent with prior evidence on relationship-specific investment and knowledge sharing in supplier–customer relationships (Minnick & Raman, 2017). The positive and statistically significant interactions

between *AI Intensity* and *Different Industry* indicate that the AI effect is stronger in cross-industry relationships.

Overall, Panel B shows that the AI effect is stronger when serving major customers involves greater adaptation and coordination demands. Together with Panel A, these results provide cross-sectional evidence consistent with the relationship-specific capability channel.

6. Relationship-Level Outcomes of AI Adoption

The evidence so far is consistent with AI strengthening relationship-specific capabilities within disclosed major-customer relationships. While sales growth captures the intensity of trade, it does not fully capture whether the relationship becomes more persistent or whether the supplier and customer become more economically aligned. We therefore examine whether this relationship-specific deepening is reflected in broader relationship-level outcomes.

6.1 Relationship Continuity

We first examine whether supplier AI investment is associated with greater relationship continuity. If AI helps suppliers better understand customer needs, adapt products or processes, and coordinate with major customers, the resulting sales gains should be accompanied by a lower likelihood that existing major-customer relationships terminate.

Following Bauer et al. (2018), we define *Termination* as an indicator equal to one if a supplier-customer relationship observed in a year is no longer disclosed in the following year, and zero otherwise. Because the dependent variable requires observing whether an existing relationship remains disclosed in the following year, we restrict the analysis to observed supplier-customer relationship-years for which subsequent-year continuation or termination can be identified, rather than using the expanded sample employed in the baseline tests.

[Table 11 Around Here]

Table 11 reports the results. Column (1) estimates a linear probability model with supplier-customer pair fixed effects and year fixed effects, consistent with the structure of our

baseline regressions. The coefficient on *AI Intensity* is negative and statistically significant, indicating that greater supplier AI investment is associated with a lower probability that an existing major-customer relationship terminates in the following year. Column (2) reports a logit model with year and industry fixed effects. The coefficient on *AI Intensity* remains negative and significant, suggesting that the result is not specific to the linear probability specification. Thus, supplier AI investment is also associated with greater relationship continuity. This finding is consistent with the view that AI strengthens relationship-specific capabilities that help suppliers maintain economically important customer ties.

6.2. Economic Alignment with Major Customers

We next examine whether supplier AI investment is associated with stronger economic alignment between suppliers and their major customers. If AI deepens major-customer relationships, the supplier and customer should become more integrated not only in sales, but also in their economic outcomes. Prior research shows that customer–supplier links transmit value-relevant information and shocks across economically connected firms (Cohen & Frazzini, 2008; Hertz et al., 2008; Lian, 2017; Pandit et al., 2011). We therefore examine supplier–customer co-movement in stock returns and earnings.

Columns (3) and (4) of Table 11 report the results. In Column (3), the dependent variable is *Partial Correlation*, measured as the partial correlation between supplier and customer stock returns over a rolling 36-month window, controlling for common exposure to aggregate market returns. This measure captures the extent to which supplier and customer returns move together beyond broad market-wide effects. The coefficient on *AI Intensity* is positive and statistically significant (0.067, $p < 0.05$), indicating that supplier AI investment is associated with stronger financial-market co-movement with major customers. We observe a similar pattern for operating performance. In Column (4), the coefficient on *AI Intensity* is

positive and statistically significant for *Earnings Correlation*, measured over a rolling 12-quarter window, suggesting closer alignment in underlying fundamentals.

Taken together, the termination and co-movement results show that supplier AI investment is associated with more durable and more economically integrated major-customer relationships. These findings reinforce the interpretation that AI is linked to relationship-specific deepening.

7. Conclusion

This study examines whether supplier AI investment broadens firms' customer base or deepens economically important major-customer relationships. We find that suppliers with greater AI investment generate higher sales within disclosed major-customer relationships. However, AI investment is not significantly associated with sales to non-major customers, the likelihood of adding newly disclosed major customers, or the number of disclosed major customers. These findings indicate that AI-related sales gains are concentrated within major-customer relationships rather than spread broadly across the customer base.

Additional evidence supports the relationship-specific deepening interpretation. AI-intensive suppliers exhibit stronger technological linkages with their major customers. The AI effect is also stronger when supplier–customer relationships are more embedded and commercially important, and when serving major customers involves greater adaptation and coordination demands. Finally, supplier AI investment is associated with lower relationship termination and stronger supplier–customer co-movement in stock returns and earnings. Together, these results suggest that AI is linked to more durable and economically integrated major-customer relationships.

Our findings contribute to a growing literature on the organizational implications of AI by shifting the focus from aggregate firm-level outcomes, such as innovation (Babina et al., 2024), labor allocation (Webb, 2019), and board governance (Hudson & Morgan, 2024), to

relationship-level product-market outcomes. We complement this literature by showing that AI-enabled product-market gains are not distributed evenly across the customer base, but are concentrated in economically important supplier–customer relationships.

We also contribute to the supplier–customer literature by identifying AI investment as a digital capability that supports relationship-specific adaptation. Prior studies emphasize the importance of relationship-specific investments, governance mechanisms, and contracting frictions in sustaining major-customer ties (Raman and Shahrur, 2008; Minnick and Raman, 2017). We show that AI investment helps suppliers use customer-specific information, support technological alignment, and maintain more durable and economically integrated relationships with key customers. In this sense, digital capabilities represent an additional channel through which suppliers can support valuable interfirm relationships.

The findings have implications for how firms and investors evaluate the strategic returns to AI investment. The benefits of AI may depend not only on its contribution to innovation, productivity, or internal efficiency, but also on how effectively firms deploy AI capabilities toward strategically important customers. In business-to-business markets, AI may therefore be especially valuable when it helps firms learn from, adapt to, and coordinate with key customers whose relationships account for a substantial share of firm value.

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Appendix

Table A1. Variable Definition

This table presents detailed definitions of the variables used in the study. Compustat item codes are provided in parentheses.

Variable	Definition
<i>MCS-to-Sales</i>	Natural logarithm of one plus supplier sales to a given major customer, scaled by the supplier's total sales (sale). Missing sales between the first and last reported sales and up to three years after the last reported sales are set to zero.
<i>MCS-to-Assets</i>	Natural logarithm of one plus supplier sales to a given major customer, scaled by the supplier's total assets (at). Missing sales between the first and last reported sales and up to three years after the last reported sales are set to zero.
<i>Non-major Customers Sales</i>	Natural logarithm of suppliers' total sales minus the sum of sales to all disclosed major customers.
<i>Add Major Customers</i>	Dummy variable equals one if the supplier adds at least one new major customer in a given year, and zero otherwise.
<i>Number Major Customers</i>	Natural logarithm of the number of disclosed major customers.
<i>AI Intensity</i>	Percentage of a firm's employees whose résumés list AI-related skills (Cognism), following Babina et al. (2024).
<i>AI Intensity BG</i>	Percentage of the firm's job postings classified as AI-related (Burning Glass), following Babina et al. (2024).
<i>ROA</i>	Operating income before depreciation (oibdp) scaled by total assets (at).
<i>Sales Growth</i>	Year-over-year change in sales (sale).
<i>Firm Size</i>	Natural logarithm of total sales (sale).
<i>Volatility</i>	Annualized standard deviation of daily stock returns.
<i>Firm Age</i>	Natural logarithm of one plus years documented in compustat.
<i>SG&A</i>	Selling, general, and administrative expenses (xsga) scaled by total assets (at).
<i>R&D</i>	Research and development expense (xrd) scaled by total assets (at). Missing values are replaced by zero.
<i>CAPEX</i>	Capital expenditures (capx) scaled by total assets (at).
<i>Leverage</i>	Long-term debt (dltt) plus debt in current liabilities (lct) over total assets (at).
<i>Dividend</i>	Dummy variable equals one if the firm pays cash dividends in the year, and 0 otherwise.
<i>Blockholder</i>	Dummy variable equals one if there is at least one institutional owner owns more than 10% of share outstanding, and 0 otherwise.
<i>Customer Asset Growth</i>	Year-over-year change in total assets (at).
<i>Customer Return</i>	Customer's three-year buy-and-hold stock return in excess of the CRSP value-weighted market index.
<i>Ln Major Customer Sales</i>	Natural logarithm of customer-specific sales without scaling.
<i>Positive Major Customer Sales</i>	Dummy variable equals one if the supplier reports any positive sales to the customer in a given year, and zero otherwise.
<i>AI-Strong Uni Hiring</i>	Index that captures a firm's exposure to AI-strong universities based on its pre-2010 hiring links to institutions classified as AI-

<i>Top 10 Uni Hiring</i>	strong according to their 2005–2009 AI research output as in Babina et al., 2024. Index that captures a firm’s exposure to elite universities through its pre-2010 hiring links as in Babina et al. (2024).
<i>With Supplier Cite Customer</i>	An indicator equal to one if the supplier cites at least one patent owned by its major customer in a given year, and zero otherwise
<i>With Cross Citation</i>	An indicator equal to one if there is at least one patent cross-citation between the supplier and its major customer in a given year, and zero otherwise
<i>Partial Correlation</i>	Partial correlation between supplier and customer stock returns over a rolling 36-month window, controlling for CRSP value-weighted index.
<i>Earnings Correlation</i>	Correlation in earnings per share between supplier and customer firms over a rolling 12-quarter window.

Table A2. Alternative Specifications Using Changes and Multi-Year Averages

This table reports robustness tests using alternative change and multi-year average specifications based on a supplier–customer–year panel for 2010–2021. The sample is constructed in the same way as in Table 5, except that Panel A reports one-year change specifications and Panel B reports three-year average specifications. $\Delta MCS\text{-}to\text{-}Sales$ is the change in the natural logarithm of one plus supplier sales to a given major customer scaled by the supplier’s total sales between year t and year $t+1$. $\Delta MCS\text{-}to\text{-}Assets$ is the change in the natural logarithm of one plus supplier sales to a given major customer scaled by total assets between year t and year $t+1$. $\Delta AI\text{ Intensity}$ is the change in the percentage of a firm’s employees whose resumes list AI-related skills over the same one-year window. All control variables in Panel A are computed as the difference between year $t+1$ and year t . *Ave MCS-to-Sales* and *Ave MCS-to-Assets* are the three-year averages of the natural logarithm of one plus supplier sales to a given major customer scaled by supplier sales and total assets, respectively. *Ave AI Intensity* is the three-year average of the percentage of a firm’s employees whose resumes list AI-related skills. All control variables in Panel B are measured as three-year averages. Supplier–customer pair fixed effects and year fixed effects are included. Standard errors are clustered at the supplier level and reported in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively. Detailed variable definitions appear in Table A1.

	(1)	(2)		(1)	(2)
	Panel A: One-year Change			Panel B: Three-year Average	
	$\Delta MCS\text{-}to\text{-}Sales$	$\Delta MCS\text{-}to\text{-}Assets$		<i>Ave MCS-to-Sales</i>	<i>Ave MCS-to-Assets</i>
$\Delta AI\text{ Intensity}$	0.014* (0.007)	0.014** (0.007)	<i>Ave AI Intensity</i>	0.047** (0.020)	0.031** (0.016)
ΔROA	-0.009 (0.011)	0.003 (0.009)	<i>Ave ROA</i>	0.012 (0.040)	0.066** (0.031)
$\Delta Sales\text{ Growth}$	0.001 (0.003)	0.002 (0.003)	<i>Ave Sales Growth</i>	0.009 (0.017)	-0.010 (0.013)
$\Delta Firm\text{ Size}$	-0.029*** (0.005)	-0.011** (0.005)	<i>Ave Firm Size</i>	-0.017* (0.009)	-0.008 (0.007)
$\Delta Volatility$	-0.034*** (0.012)	-0.013 (0.012)	<i>Ave Volatility</i>	-0.078* (0.045)	-0.035 (0.054)
$\Delta Firm\text{ Age}$	0.022 (0.038)	-0.013 (0.038)	<i>Ave Firm Age</i>	-0.047** (0.020)	-0.047** (0.021)
$\Delta SG\&A$	0.007 (0.013)	-0.007 (0.015)	<i>Ave SG\&A</i>	-0.035 (0.046)	0.068 (0.048)
$\Delta R\&D$	0.003 (0.028)	0.023 (0.025)	<i>Ave R\&D</i>	0.115 (0.119)	0.043 (0.102)
$\Delta CAPEX$	-0.031 (0.022)	-0.027* (0.015)	<i>Ave CAPEX</i>	-0.015 (0.055)	-0.074 (0.056)
$\Delta Leverage$	0.005 (0.004)	-0.007* (0.004)	<i>Ave Leverage</i>	0.028* (0.015)	0.010 (0.016)
$\Delta Dividend$	0.002 (0.003)	0.004 (0.004)	<i>Ave Dividend</i>	0.012 (0.009)	0.007 (0.010)
$\Delta Blockholder$	0.000 (0.002)	0.000 (0.002)	<i>Ave Blockholder</i>	-0.007 (0.004)	-0.015*** (0.005)
$\Delta Customer\text{ Firm Size}$	0.001 (0.003)	-0.000 (0.002)	<i>Ave Customer Firm Size</i>	0.018* (0.010)	0.010 (0.007)
$\Delta Customer\text{ ROA}$	0.007 (0.008)	0.010 (0.007)	<i>Ave Customer ROA</i>	0.022 (0.023)	0.037 (0.024)
$\Delta Customer\text{ R\&D}$	0.013 (0.013)	0.015 (0.012)	<i>Ave Customer R\&D</i>	0.164*** (0.060)	0.116* (0.063)
$\Delta Customer\text{ Leverage}$	-0.000 (0.003)	0.001 (0.003)	<i>Ave Customer Leverage</i>	0.007 (0.011)	0.011 (0.013)
$\Delta Customer\text{ Asset Growth}$	-0.001 (0.002)	-0.001 (0.002)	<i>Ave Customer Asset Growth</i>	-0.002 (0.009)	-0.010 (0.012)

<i>Δ Customer Return</i>	-0.000 (0.001)	-0.001 (0.001)	<i>Ave Customer Return</i>	-0.003 (0.004)	-0.004 (0.004)
<i>Supplier- Customer FE</i>	Yes	Yes	<i>Supplier-Customer FE</i>	Yes	Yes
<i>Year FE</i>	Yes	Yes	<i>Year FE</i>	Yes	Yes
<i>Constant</i>	-0.006*** (0.002)	-0.005** (0.002)	<i>Constant</i>	0.125 (0.114)	0.122 (0.089)
<i>Observations</i>	3,690	3,690	<i>Observations</i>	2,663	2,663
<i>Adjusted R- squared</i>	-0.032	-0.055	<i>Adjusted R- squared</i>	0.824	0.854

Table A3. Additional Robustness Tests for Broader Customer-Base Expansion

This table reports additional robustness tests examining whether supplier AI investment is associated with broader customer-base expansion, using the supplier–year panel for 2010–2021. The sample is constructed in the same way as in Table 3. The dependent variable in Column (1), *Non-MCS-to-Assets*, is supplier sales not attributable to disclosed major customers, scaled by total assets. The dependent variable in Column (2), *Non-major Customers Sales*, is the natural logarithm of one plus supplier sales not attributable to disclosed major customers. The dependent variable in Column (3), *Add Major Customers*, is an indicator equal to one if the supplier adds at least one newly disclosed major customer, and zero otherwise. The dependent variable in Column (4), *Number Major Customers*, is the natural logarithm of one plus the number of disclosed major customers. Column (5) uses the three-year change in the number of disclosed major customers as the dependent variable. *AI Intensity* is measured as the percentage of a firm’s employees whose resumes list AI-related skills, following Babina et al. (2024). *AI Intensity BG* is the share of AI-related job postings from Burning Glass. Δ *AI Intensity* is the three-year change in supplier AI intensity. Columns (1)–(4) include the same control variables as in Table 3. In Column (5), the control variables are measured as three-year changes. Standard errors are clustered at the supplier level and reported in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively. Detailed variable definitions appear in Table A1.

	(1)	(2)	(3)	(4)	(5)
	<i>Non-MCS-to-Assets</i>	<i>Non-major Customers Sales</i>	<i>Add Major Customers</i>	<i>Number Major Customers</i>	Δ <i>Number Major Customers</i>
<i>AI Intensity</i>	0.061 (0.100)				
<i>AI Intensity BG</i>		-0.017 (0.013)	0.023 (0.054)	0.027 (0.030)	
Δ <i>AI Intensity</i>					-0.022 (0.195)
<i>ROA</i>	0.433*** (0.124)	-0.043 (0.092)	-0.101 (0.103)	0.014 (0.075)	0.059 (0.236)
<i>Sales Growth</i>	0.017 (0.019)	0.040 (0.034)	-0.104*** (0.033)	-0.061** (0.029)	-0.048 (0.053)
<i>Firm Size</i>	0.165*** (0.031)	1.098*** (0.033)	0.137** (0.054)	0.065 (0.045)	0.041 (0.117)
<i>Volatility</i>	0.135 (0.209)	0.150* (0.078)	0.209 (0.255)	0.015 (0.177)	-1.004* (0.546)
<i>Firm Age</i>	0.183** (0.083)	0.070 (0.060)	-0.448** (0.209)	-0.190 (0.193)	1.594 (1.123)
<i>SG&A</i>	0.772*** (0.155)	0.246** (0.097)	0.098 (0.210)	0.127 (0.131)	0.232 (0.251)
<i>R&D</i>	0.184 (0.614)	-0.558** (0.238)	-0.201 (0.775)	-0.300 (0.470)	0.047 (1.017)
<i>CAPEX</i>	-0.344** (0.166)	-0.085 (0.130)	0.252 (0.351)	-0.050 (0.254)	-0.140 (0.559)
<i>Leverage</i>	-0.343*** (0.052)	-0.065** (0.030)	0.013 (0.064)	0.088* (0.053)	0.052 (0.095)
<i>Dividend</i>	-0.022 (0.030)	0.005 (0.010)	0.065 (0.069)	-0.043 (0.063)	-0.050 (0.110)
<i>Blockholder</i>	-0.009 (0.018)	-0.005 (0.008)	0.003 (0.030)	0.003 (0.020)	-0.000 (0.055)
<i>Supplier FE</i>	Yes	Yes	Yes	Yes	Yes
<i>Year FE</i>	Yes	Yes	Yes	Yes	Yes
<i>Constant</i>	-0.767** (0.307)	-0.977*** (0.272)	0.505 (0.649)	1.135** (0.535)	-0.059 (0.203)
<i>Observations</i>	1,744	949	951	951	2,425
<i>Adjusted R-squared</i>	0.917	0.998	0.184	0.819	0.511

Table A4. Instrumental Variable Tests for Broader Customer-Base Expansion

This table reports baseline and instrumental variable regressions examining whether supplier AI investment is associated with broader customer-base expansion, using the supplier–year panel for 2010–2021. The dependent variable in Columns (1) and (5), *Non-major Customers Sales*, is the natural logarithm of one plus supplier sales not attributable to disclosed major customers. The dependent variable in Columns (2) and (6), *Add Major Customers*, is an indicator equal to one if the supplier adds at least one newly disclosed major customer, and zero otherwise. The dependent variable in Columns (3) and (7), *Number Major Customers*, is the natural logarithm of one plus the number of disclosed major customers. Columns (1)–(3) report OLS regressions using supplier fixed effects, customer fixed effects, and year fixed effects. Column (4) reports the first-stage regression. Columns (5)–(7) report the second-stage IV regressions, instrumenting *AI Intensity* with *AI-Strong Uni Hiring*, a continuous index that captures a firm’s exposure to AI-strong universities based on its pre-2010 hiring links to institutions classified as AI-strong according to their 2005–2009 AI research output, following Babina et al. (2024). Standard errors are clustered at the supplier level and reported in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively. Detailed variable definitions appear in Table A1.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	<i>Baseline: Supplier, Customer, Year FE</i>			<i>IV 1st Stage</i>	<i>IV 2nd Stage</i>		
	<i>Non-major Customers Sales</i>	<i>Add Major Customers</i>	<i>Number Major Customers</i>	<i>AI Intensity</i>	<i>Non-major Customers Sales</i>	<i>Add Major Customers</i>	<i>Number Major Customers</i>
<i>AI Intensity</i>	-0.107* (0.065)	-0.008 (0.033)	-0.132 (0.091)				
<i>AI-Strong Uni Hiring</i>				2.267*** (0.311)			
<i>Instrumented AI Intensity</i>					0.016 (0.186)	0.124 (0.201)	0.124 (0.490)
<i>ROA</i>	-0.064 (0.077)	-0.036 (0.053)	0.022 (0.093)	0.132*** (0.034)	-0.090 (0.099)	-0.054 (0.061)	-0.006 (0.118)
<i>Sales Growth</i>	0.023 (0.017)	-0.014 (0.015)	-0.013 (0.032)	0.036** (0.016)	0.017 (0.024)	-0.018 (0.020)	-0.034 (0.042)
<i>Firm Size</i>	1.042*** (0.013)	0.009 (0.007)	0.031** (0.015)	0.013*** (0.005)	1.041*** (0.016)	0.006 (0.008)	0.027 (0.018)
<i>Volatility</i>	-0.033 (0.118)	-0.100 (0.131)	-0.100 (0.198)	0.213** (0.097)	-0.054 (0.119)	-0.122 (0.135)	-0.143 (0.229)
<i>Firm Age</i>	-0.027 (0.020)	0.001 (0.017)	-0.000 (0.037)	-0.020** (0.009)	-0.021 (0.021)	0.002 (0.020)	0.005 (0.041)
<i>SG&A</i>	0.132 (0.093)	-0.059 (0.068)	0.054 (0.121)	-0.131*** (0.043)	0.144* (0.086)	-0.041 (0.073)	0.094 (0.135)
<i>R&D</i>	-0.294* (0.153)	0.344** (0.149)	0.038 (0.253)	1.001*** (0.085)	-0.416 (0.256)	0.204 (0.244)	-0.218 (0.548)
<i>CAPEX</i>	0.149 (0.215)	0.516*** (0.179)	0.370 (0.320)	-0.236** (0.114)	0.215 (0.231)	0.571*** (0.205)	0.528 (0.362)
<i>Leverage</i>	-0.018	-0.030	0.070	-0.089***	-0.010	-0.018	0.088

	(0.040)	(0.034)	(0.065)	(0.023)	(0.051)	(0.037)	(0.075)
<i>Dividend</i>	0.043*	-0.029	-0.113**	-0.015	0.042*	-0.024	-0.109**
	(0.022)	(0.024)	(0.050)	(0.015)	(0.023)	(0.024)	(0.050)
<i>Blockholder</i>	0.023	0.031	-0.017	-0.007	0.024	0.031	-0.011
	(0.031)	(0.021)	(0.036)	(0.013)	(0.031)	(0.021)	(0.037)
<i>Supplier FE</i>	Yes	Yes	Yes	Yes	Yes	Yes	Yes
<i>Customer FE</i>	Yes	Yes	Yes	Yes	Yes	Yes	Yes
<i>Year FE</i>	Yes	Yes	Yes	Yes	Yes	Yes	Yes
<i>Constant</i>	-0.300**	0.035	0.823***	-0.008	-0.324**	0.037	0.796***
	(0.137)	(0.071)	(0.168)	(0.050)	(0.139)	(0.078)	(0.180)
<i>Observations</i>	1,716	1,718	1,718	1,695	1,693	1,695	1,695
<i>Adjusted R-squared</i>	0.973	0.013	0.130	0.267	0.973	0.014	0.126

Table A5. Entropy-Balanced Tests for Broader Customer-Base Expansion

This table reports entropy-balanced regressions examining whether supplier AI investment is associated with broader customer-base expansion, using the supplier–year panel for 2010–2021. The entropy-balancing weights are constructed using the same supplier characteristics as in Table 7. The dependent variable in Column (1), *Non-major Customers Sales*, is the natural logarithm of one plus supplier sales not attributable to disclosed major customers. The dependent variable in Column (2), *Add Major Customers*, is an indicator equal to one if the supplier adds at least one newly disclosed major customer, and zero otherwise. The dependent variable in Column (3), *Number Major Customers*, is the natural logarithm of one plus the number of disclosed major customers. *AI Intensity* is measured as the percentage of a firm’s employees whose resumes list AI-related skills, following Babina et al. (2024). Supplier fixed effects and year fixed effects are included. Standard errors are clustered at the supplier level and reported in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively. Detailed variable definitions appear in Table A1.

	(1)	(2)	(3)
	<i>Non-major Customers Sales</i>	<i>Add Major Customers</i>	<i>Number Major Customers</i>
<i>AI Intensity</i>	-0.101 (0.062)	-0.010 (0.035)	-0.109 (0.092)
<i>ROA</i>	-0.043 (0.074)	0.077 (0.056)	0.120 (0.089)
<i>Sales Growth</i>	0.017 (0.015)	-0.035 (0.027)	-0.034 (0.042)
<i>Firm Size</i>	1.042*** (0.013)	-0.004 (0.010)	-0.003 (0.020)
<i>Volatility</i>	-0.036 (0.107)	0.134 (0.167)	0.001 (0.278)
<i>Firm Age</i>	-0.025 (0.018)	0.011 (0.019)	-0.000 (0.044)
<i>SG&A</i>	0.151 (0.092)	-0.114 (0.079)	-0.027 (0.150)
<i>R&D</i>	-0.297** (0.145)	0.537*** (0.204)	0.214 (0.249)
<i>CAPEX</i>	0.138 (0.221)	0.499** (0.245)	0.887* (0.516)
<i>Leverage</i>	-0.026 (0.034)	0.013 (0.043)	0.151* (0.083)
<i>Dividend</i>	0.038* (0.022)	-0.016 (0.024)	-0.083 (0.057)
<i>Blockholder</i>	0.018 (0.027)	0.025 (0.026)	-0.051 (0.041)
<i>Supplier FE</i>	Yes	Yes	Yes
<i>Year FE</i>	Yes	Yes	Yes
<i>Constant</i>	-0.301** (0.127)	0.041 (0.106)	1.015*** (0.224)
<i>Observations</i>	1,736	1,738	1,738
<i>Adjusted R-squared</i>	0.973	0.040	0.100

Tables

Table 1. Descriptive Statistics

This table reports summary statistics, number of observations (Obs), mean (Mean), standard deviation (Std), 25th percentile (P25), median (Median), and 75th percentile (P75)—for the main variables used in the regressions, based on the supplier–customer–year panel for 2010–2021. *MCS-to-Sales* is the natural logarithm of one plus supplier sales to a given major customer, scaled by the supplier’s total sales (sale). Missing sales between the first and last reported sales and up to three years after the last reported sales are set to zero. *MCS-to-Assets* is the natural logarithm of one plus supplier sales to a given major customer, scaled by the supplier’s total assets (at). Missing sales between the first and last reported sales and up to three years after the last reported sales are set to zero. *AI Intensity* is the percentage of a firm’s employees whose resumes list AI-related skills as in Babina et al. (2024). *AI Intensity BG* is the percentage of the firm’s job postings classified as AI-related as in Babina et al. (2024). *ROA* is operating income before depreciation scaled by total assets. *Sales Growth* is the year-over-year change in sales. *Firm Size* is the natural logarithm of total sales. *Volatility* is the annualized standard deviation of daily stock returns. *Firm Age* is the natural logarithm of one plus years documented in Compustat. *SG&A* is selling, general, and administrative expenses scaled by total assets. *R&D* is research and development expense scaled by total assets. Missing values are replaced by zero. *CAPEX* is capital expenditure scaled by total assets. *Leverage* is long-term debt plus debt in current liabilities over total assets. *Dividend* equals one if the firm pays cash dividends in the year, and 0 otherwise. *Blockholder* equals one if there is at least one institutional owner owns more than 10% of share outstanding, and zero otherwise. *Customer Asset Growth* is the year-over-year change in total assets. *Customer Return* is the customer’s three-year buy-and-hold stock return in excess of the CRSP value-weighted market index. Detailed variable definitions can be found in Table A1.

Variable	Obs	Mean	Std	P25	Median	P75
<i>MCS-to-Sales</i>	3,902	0.077	0.101	0.000	0.042	0.105
<i>MCS-to-Assets</i>	3,902	0.082	0.096	0.000	0.060	0.106
<i>AI Intensity</i>	3,902	0.094	0.282	0.000	0.000	0.022
<i>ROA</i>	3,902	0.051	0.356	0.012	0.124	0.205
<i>Sales Growth</i>	3,902	0.140	0.638	-0.086	0.022	0.161
<i>Firm Size</i>	3,902	6.511	1.897	5.438	6.648	7.597
<i>Volatility</i>	3,902	0.125	0.081	0.069	0.103	0.157
<i>Firm Age</i>	3,902	2.814	0.894	2.197	2.944	3.466
<i>SG&A</i>	3,902	0.214	0.298	0.022	0.118	0.294
<i>R&D</i>	3,902	0.076	0.152	0.000	0.000	0.093
<i>CAPEX</i>	3,902	0.045	0.073	0.003	0.020	0.053
<i>Leverage</i>	3,902	0.466	0.433	0.230	0.387	0.566
<i>Dividend</i>	3,902	0.468	0.499	0.000	0.000	1.000
<i>Blockholder</i>	3,902	0.632	0.482	0.000	1.000	1.000
<i>Customer Firm Size</i>	3,902	8.289	2.873	6.782	8.758	10.250
<i>Customer ROA</i>	3,902	0.029	0.579	0.057	0.134	0.208
<i>Customer R&D</i>	3,902	0.057	0.141	0.000	0.000	0.038
<i>Customer Leverage</i>	3,902	0.652	0.973	0.351	0.502	0.693
<i>Customer Asset Growth</i>	3,902	0.128	0.498	-0.049	0.029	0.136
<i>Customer Return</i>	3,902	0.388	0.962	-0.201	0.192	0.700

Table 2. AI Investment and Sales to Major Customers

This table reports regressions of sales to major customers on firm AI investment using the supplier–customer–year panel for 2010–2021. Missing customer sales between the first and last year of a disclosed supplier–customer relationship are set to zero. The relationship window is extended by up to three years after the last reported sale. The dependent variable in Column (1), *MCS-to-Sales*, is the natural logarithm of one plus supplier sales to a given major customer, scaled by the supplier’s total sales. The dependent variable in Column (2), *MCS-to-Assets*, is the natural logarithm of one plus supplier sales to a given major customer, scaled by the supplier’s total assets. *AI Intensity* is the percentage of a firm’s employees whose resumes list AI-related skills as in Babina et al. (2024). Supplier–customer pair fixed effects and year fixed effects are included. Standard errors are clustered at the supplier level and reported in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively. Detailed variable definitions appear in Table A1.

	(1)	(2)
	<i>MCS-to-Sales</i>	<i>MCS-to-Assets</i>
<i>AI Intensity</i>	0.035*** (0.012)	0.032*** (0.012)
<i>ROA</i>	-0.012 (0.015)	0.019 (0.014)
<i>Sales Growth</i>	0.003 (0.003)	-0.000 (0.002)
<i>Firm Size</i>	-0.014*** (0.005)	-0.004 (0.004)
<i>Volatility</i>	-0.074*** (0.018)	-0.032* (0.019)
<i>Firm Age</i>	-0.047*** (0.017)	-0.040*** (0.015)
<i>SG&A</i>	-0.002 (0.020)	0.009 (0.017)
<i>R&D</i>	-0.003 (0.053)	-0.035 (0.046)
<i>CAPEX</i>	-0.006 (0.025)	-0.026 (0.021)
<i>Leverage</i>	0.008 (0.006)	0.002 (0.006)
<i>Dividend</i>	0.006 (0.005)	0.005 (0.007)
<i>Blockholder</i>	-0.001 (0.002)	-0.002 (0.003)
<i>Customer Firm Size</i>	0.004 (0.005)	-0.000 (0.003)
<i>Customer ROA</i>	0.007 (0.011)	0.014 (0.010)
<i>Customer R&D</i>	0.049** (0.022)	0.057** (0.025)
<i>Customer Leverage</i>	-0.000 (0.004)	0.002 (0.003)
<i>Customer Asset Growth</i>	-0.003 (0.003)	-0.005* (0.003)
<i>Customer Return</i>	0.001 (0.001)	-0.001 (0.001)
<i>Supplier-Customer FE</i>	Yes	Yes
<i>Year FE</i>	Yes	Yes
<i>Constant</i>	0.244*** (0.068)	0.185*** (0.057)
<i>Observations</i>	3,902	3,902
<i>Adjusted R-squared</i>	0.656	0.690

Table 3. Investment and Customer-Base Dynamics: Non-Major Sales and Major-Customer Expansion

This table reports regressions of customer-base outcomes on firm-level AI investment using the supplier–year panel for 2010–2021. The dependent variable in Column (1), *Non-major Customer Sales*, is the natural logarithm of one plus supplier sales not attributable to disclosed major customers. The dependent variable in Column (2), *Add Major Customers*, is an indicator equal to one if the supplier adds at least one newly disclosed major customer, and zero otherwise. The dependent variable in Column (3), *Number Major Customers*, is the natural logarithm of one plus the number of disclosed major customers. AI Intensity is measured as the percentage of a firm’s employees whose resumes list AI-related skills, following Babina et al. (2024). Supplier fixed effects and year fixed effects are included. Standard errors are clustered at the supplier level and reported in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively. Detailed variable definitions appear in Table A1.

	(1)	(2)	(3)
	<i>Non-major Customers Sales</i>	<i>Add Major Customers</i>	<i>Number Major Customers</i>
<i>AI Intensity</i>	-0.054 (0.033)	-0.055 (0.083)	0.057 (0.066)
<i>ROA</i>	0.032 (0.088)	-0.102* (0.058)	0.013 (0.046)
<i>Sales Growth</i>	0.001 (0.024)	-0.020 (0.017)	-0.006 (0.017)
<i>Firm Size</i>	1.082*** (0.030)	0.063** (0.031)	-0.002 (0.032)
<i>Volatility</i>	0.195** (0.085)	-0.225 (0.149)	-0.078 (0.123)
<i>Firm Age</i>	0.004 (0.092)	-0.250** (0.102)	-0.085 (0.115)
<i>SG&A</i>	0.147 (0.092)	0.077 (0.104)	0.078 (0.108)
<i>R&D</i>	-0.211 (0.243)	-0.239 (0.276)	-0.529 (0.366)
<i>CAPEX</i>	-0.026 (0.107)	0.153 (0.193)	-0.080 (0.143)
<i>Leverage</i>	-0.032 (0.022)	-0.017 (0.042)	0.092** (0.042)
<i>Dividend</i>	-0.006 (0.016)	0.071 (0.046)	-0.016 (0.045)
<i>Blockholder</i>	0.011 (0.009)	0.014 (0.022)	0.007 (0.019)
<i>Supplier FE</i>	Yes	Yes	Yes
<i>Year FE</i>	Yes	Yes	Yes
<i>Constant</i>	-0.688*** (0.201)	0.462 (0.327)	1.292*** (0.359)
<i>Observations</i>	1,741	1,744	1,744
<i>Adjusted R-squared</i>	0.988	0.138	0.811

Table 3. AI Investment and Sales to Major Customers: Alternative Treatments of Missing Customer Sales

This table reports regressions of sales to major customers on firm AI investment, using alternative treatment on missing customer sales in the Compustat Segment files, based on a supplier–customer–year panel for 2010–2021. The dependent variables in Columns (1), (3), (5), and (7) are *MCS-to-Sales*, which is the natural logarithm of one plus supplier sales to a given major customer, scaled by the supplier’s total sales. The dependent variables in Columns (2), (4), (6), and (8) are *MCS-to-Assets*, which is the natural logarithm of one plus supplier sales to a given major customer, scaled by the supplier’s total assets. Columns (1) and (2) drop observations with missing customer sales, Columns (3) and (4) extend one year of zero sales after the last reported sale, Columns (5) and (6) extend two years of zero sales, Columns (7) and (8) set missing sales to 10% before relationship end. *AI Intensity* is the percentage of a firm’s employees whose resumes list AI-related skills as in Babina et al. (2024). Supplier–customer pair fixed effects and year fixed effects are included. Standard errors are clustered at the supplier level and reported in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively. Detailed variable definitions appear in Table A1.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	<i>Remove Missing Sales</i>		<i>Add Only 1 Year of Missing Sales to the End of Each Relationship</i>		<i>Add Only 2 Year of Missing Sales to the End of Each Relationship</i>		<i>Set Missing Sales to 10%</i>	
	<i>MCS-to-Sales</i>	<i>MCS-to-Assets</i>	<i>MCS-to-Sales</i>	<i>MCS-to-Assets</i>	<i>MCS-to-Sales</i>	<i>MCS-to-Assets</i>	<i>MCS-to-Sales</i>	<i>MCS-to-Assets</i>
<i>AI Intensity</i>	0.035** (0.016)	0.023* (0.013)	0.037*** (0.014)	0.023** (0.011)	0.037*** (0.014)	0.027** (0.012)	0.017*** (0.006)	0.016** (0.007)
<i>ROA</i>	-0.017 (0.017)	0.018 (0.014)	-0.027 (0.018)	0.020 (0.016)	-0.016 (0.016)	0.021 (0.015)	-0.007 (0.007)	0.030*** (0.008)
<i>Sales Growth</i>	0.007 (0.005)	0.002 (0.004)	0.004 (0.005)	-0.000 (0.003)	0.005 (0.005)	0.001 (0.003)	0.005** (0.002)	0.000 (0.002)
<i>Firm Size</i>	-0.023*** (0.007)	-0.008 (0.007)	-0.023*** (0.008)	-0.008 (0.006)	-0.018*** (0.006)	-0.006 (0.005)	-0.031*** (0.003)	-0.013*** (0.003)
<i>Volatility</i>	-0.097*** (0.028)	-0.027 (0.029)	-0.087*** (0.023)	-0.031 (0.024)	-0.088*** (0.020)	-0.033* (0.020)	-0.070*** (0.014)	-0.020 (0.014)
<i>Firm Age</i>	-0.059*** (0.019)	-0.050** (0.021)	-0.055*** (0.017)	-0.052*** (0.018)	-0.051*** (0.017)	-0.045*** (0.016)	-0.013 (0.008)	-0.017** (0.009)
<i>SG&A</i>	-0.038* (0.023)	0.008 (0.026)	-0.007 (0.026)	0.004 (0.022)	-0.006 (0.023)	0.009 (0.018)	-0.044*** (0.016)	-0.009 (0.016)
<i>R&D</i>	0.084 (0.057)	0.014 (0.054)	-0.015 (0.068)	-0.031 (0.058)	-0.004 (0.058)	-0.037 (0.049)	0.099*** (0.030)	0.044 (0.032)
<i>CAPEX</i>	0.022 (0.031)	-0.025 (0.029)	-0.021 (0.030)	-0.023 (0.025)	-0.011 (0.026)	-0.025 (0.021)	0.038** (0.019)	0.024 (0.020)
<i>Leverage</i>	0.017* (0.010)	-0.002 (0.012)	0.017* (0.009)	-0.000 (0.010)	0.009 (0.007)	0.000 (0.006)	0.017*** (0.005)	-0.003 (0.005)
<i>Dividend</i>	0.008 (0.008)	0.008 (0.012)	0.007 (0.006)	0.006 (0.009)	0.006 (0.006)	0.005 (0.008)	0.000 (0.004)	-0.002 (0.004)
<i>Blockholder</i>	-0.003 (0.003)	-0.008** (0.004)	-0.001 (0.002)	-0.003 (0.003)	-0.001 (0.002)	-0.003 (0.003)	-0.001 (0.002)	-0.006*** (0.002)

<i>Customer Firm Size</i>	0.003 (0.007)	0.002 (0.004)	0.003 (0.005)	-0.000 (0.003)	0.004 (0.005)	-0.001 (0.003)	0.005** (0.002)	0.004 (0.003)
<i>Customer ROA</i>	0.005 (0.019)	0.022 (0.017)	0.011 (0.016)	0.020 (0.013)	0.011 (0.015)	0.020 (0.013)	-0.017* (0.009)	-0.004 (0.010)
<i>Customer R&D</i>	0.057 (0.040)	0.074 (0.054)	0.071** (0.031)	0.066** (0.033)	0.061** (0.025)	0.064** (0.027)	0.014 (0.025)	-0.009 (0.026)
<i>Customer Leverage</i>	0.008 (0.006)	0.009* (0.005)	-0.002 (0.004)	0.002 (0.004)	-0.002 (0.004)	0.001 (0.004)	0.003 (0.005)	0.007 (0.005)
<i>Customer Asset Growth</i>	-0.006 (0.005)	-0.007 (0.005)	-0.003 (0.004)	-0.005 (0.004)	-0.002 (0.003)	-0.005 (0.003)	0.003 (0.004)	-0.000 (0.004)
<i>Customer Return</i>	0.000 (0.002)	-0.001 (0.002)	0.001 (0.002)	-0.000 (0.002)	0.001 (0.001)	-0.001 (0.001)	-0.000 (0.001)	-0.000 (0.001)
<i>Supplier-Customer FE</i>	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
<i>Year FE</i>	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
<i>Constant</i>	0.386*** (0.100)	0.248*** (0.090)	0.352*** (0.080)	0.254*** (0.072)	0.295*** (0.072)	0.222*** (0.062)	0.316*** (0.036)	0.210*** (0.037)
<i>Observations</i>	2,101	2,101	2,993	2,993	3,505	3,505	2,247	2,247
<i>Adjusted R-squared</i>	0.728	0.762	0.690	0.720	0.665	0.703	0.780	0.823

Table 5. Three-Year Changes in AI Investment and Sales to Major Customers

This table reports regressions of changes in major customer sales on changes in AI investment and firm characteristics, measured from year t to $t+3$, based on a supplier–customer–year panel for 2010–2021. Missing customer sales between the first and last year of a disclosed supplier–customer relationship are set to zero. The relationship window is extended by up to three years after the last reported sale. The dependent variable in column (1), $\Delta \text{MCS-to-Sales}$, is the change in the natural logarithm of one plus supplier sales to a given major customer scaled by the supplier’s total sales between year t and $t+3$. Column (2) uses $\Delta \text{MCS-to-Assets}$, defined as the change in the natural logarithm of one plus supplier sales to a given major customer scaled by total assets. $\Delta \text{AI Intensity}$ is the change in the percentage of a firm’s employees whose resumes list AI-related skills over the three-year window. All control variables are computed as the difference between year $t+3$ and year t . Supplier–customer pair fixed effects and year fixed effects are included. Standard errors are clustered at the supplier level and reported in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively. Detailed variable definitions appear in Table A1.

	(1)	(2)
	$\Delta \text{MCS-to-Sales}$	$\Delta \text{MCS-to-Assets}$
$\Delta \text{AI Intensity}$	0.019*	0.020*
	(0.011)	(0.011)
ΔROA	-0.018	0.011
	(0.026)	(0.018)
$\Delta \text{Sales Growth}$	0.000	-0.001
	(0.006)	(0.005)
$\Delta \text{Firm Size}$	-0.026**	-0.005
	(0.013)	(0.016)
$\Delta \text{Volatility}$	-0.069**	-0.031
	(0.027)	(0.023)
$\Delta \text{Firm Age}$	0.026	-0.020
	(0.045)	(0.047)
$\Delta \text{SG\&A}$	0.003	0.047
	(0.032)	(0.043)
$\Delta \text{R\&D}$	0.079	0.059
	(0.118)	(0.095)
ΔCAPEX	-0.027	-0.080**
	(0.035)	(0.032)
$\Delta \text{Leverage}$	0.020**	-0.001
	(0.009)	(0.012)
$\Delta \text{Dividend}$	-0.005	-0.003
	(0.008)	(0.010)
$\Delta \text{Blockholder}$	-0.001	-0.004
	(0.003)	(0.005)
$\Delta \text{Customer Firm Size}$	0.008	0.009
	(0.006)	(0.006)
$\Delta \text{Customer ROA}$	0.006	0.012
	(0.011)	(0.012)
$\Delta \text{Customer R\&D}$	0.010	0.064
	(0.069)	(0.040)
$\Delta \text{Customer Leverage}$	0.004	0.004
	(0.004)	(0.005)
$\Delta \text{Customer Asset Growth}$	-0.005	-0.006
	(0.004)	(0.004)
$\Delta \text{Customer Return}$	0.001	0.001
	(0.001)	(0.001)
<i>Supplier-Customer FE</i>	Yes	Yes
<i>Year FE</i>	Yes	Yes
<i>Constant</i>	-0.018**	-0.014*
	(0.008)	(0.008)
<i>Observations</i>	2,004	2,004
<i>Adjusted R-squared</i>	0.280	0.278

Table 6. Alternative Measures of Sales to Major Customers and AI Investment

This table reports regressions of sales to major customers on firm AI investment, using alternative measures, based on a supplier–customer–year panel for 2010–2021. Missing customer sales between the first and last year of a disclosed supplier–customer relationship are set to zero. The relationship window is extended by up to three years after the last reported sale. Panel A explores alternative ways to measure major-customer sales. Column (1) uses *Ln Major Customer Sales*, the natural logarithm of customer-specific sales without scaling. Column (2) uses an indicator for *Positive Major Customer Sales*, equal to one if the supplier reports any positive sales to the customer in a given year, and zero otherwise. *AI Intensity* is the percentage of a firm’s employees whose resumes list AI-related skills as in Babina et al. (2024). Panel B uses an alternative measure of AI investment. *AI Intensity BG* is the percentage of the firm’s job postings classified as AI-related from Burning Glass as in Babina et al. (2024). The dependent variable in column (3), *MCS-to-Sales*, is the natural logarithm of one plus supplier sales to a given major customer, scaled by the supplier’s total sales. The dependent variable in column (4), *MCS-to-Assets*, is the natural logarithm of one plus supplier sales to a given major customer, scaled by the supplier’s total assets. Supplier–customer pair fixed effects and year fixed effects are included. Standard errors are clustered at the supplier level and reported in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively. Detailed variable definitions appear in Table A1.

	(1)	(2)	(3)	(4)
	<i>Panel A: Alternative Measures for Sales to Major Customers</i>		<i>Panel B: Alternative Measures for AI Investment</i>	
	<i>Ln Major Customer Sales</i>	<i>Positive Major Customer Sales</i>	<i>MCS-to-Sales</i>	<i>MCS-to-Assets</i>
<i>AI Intensity</i>	0.598** (0.249)	0.154** (0.060)		
<i>AI Intensity BG</i>			0.009** (0.004)	0.007* (0.004)
<i>ROA</i>	0.008 (0.335)	-0.069 (0.086)	-0.015* (0.009)	0.003 (0.010)
<i>Sales Growth</i>	-0.030 (0.078)	-0.017 (0.019)	0.002 (0.003)	0.001 (0.003)
<i>Firm Size</i>	0.300** (0.151)	0.073** (0.033)	-0.019*** (0.003)	-0.004 (0.004)
<i>Volatility</i>	-1.458** (0.642)	-0.222 (0.142)	-0.030* (0.017)	-0.012 (0.018)
<i>Firm Age</i>	-0.787 (0.551)	-0.249** (0.124)	-0.041*** (0.015)	-0.053*** (0.016)
<i>SG&A</i>	0.281 (0.522)	0.098 (0.134)	0.010 (0.017)	-0.006 (0.018)
<i>R&D</i>	-0.899 (0.893)	-0.359 (0.257)	-0.001 (0.038)	0.020 (0.041)
<i>CAPEX</i>	0.183 (1.000)	-0.090 (0.221)	0.038* (0.023)	0.010 (0.024)
<i>Leverage</i>	-0.065 (0.203)	0.001 (0.043)	-0.000 (0.006)	-0.001 (0.006)
<i>Dividend</i>	0.476**	0.093*	0.003	0.004

	(0.233)	(0.054)	(0.005)	(0.005)
<i>Blockholder</i>	0.053	0.001	0.000	0.001
	(0.089)	(0.020)	(0.002)	(0.002)
<i>Customer Firm Size</i>	0.125	0.005	0.007**	0.003
	(0.128)	(0.026)	(0.003)	(0.003)
<i>Customer ROA</i>	0.306	0.070	0.000	0.004
	(0.302)	(0.073)	(0.010)	(0.011)
<i>Customer R&D</i>	1.160	0.297	0.064*	0.081**
	(0.807)	(0.198)	(0.037)	(0.039)
<i>Customer Leverage</i>	-0.074	-0.016	0.005	0.005
	(0.117)	(0.028)	(0.004)	(0.005)
<i>Customer Asset Growth</i>	-0.105	-0.029	-0.003	-0.007
	(0.094)	(0.022)	(0.004)	(0.004)
<i>Customer Return</i>	0.042	0.012	0.001	0.001
	(0.041)	(0.009)	(0.001)	(0.001)
<i>Supplier-Customer FE</i>	Yes	Yes	Yes	Yes
<i>Year FE</i>	Yes	Yes	Yes	Yes
<i>Constant</i>	0.598	0.525	0.222***	0.195***
	(2.071)	(0.471)	(0.053)	(0.056)
<i>Observations</i>	3,902	3,902	2,461	2,461
<i>Adjusted R-squared</i>	0.624	0.565	0.639	0.663

Table 7. AI Investment and Sales to Major Customers: IV Strategy

This table reports baseline and instrumental variable regressions of sales to major customers on firm AI investment using the supplier–customer–year panel for 2010–2021. Missing customer sales between the first and last year of a disclosed supplier–customer relationship are set to zero. The relationship window is extended by up to three years after the last reported sale. Columns (1) and (2) follow Chen et al. (2021) to use supplier fixed effects, customer fixed effects, and year fixed effects. Columns (3) to (5) report regressions of the IV approach, instrumenting *AI Intensity* with *AI-Strong Uni Hiring*, a continuous index that captures a firm’s exposure to AI-strong universities based on its pre-2010 hiring links to institutions classified as AI-strong according to their 2005–2009 AI research output as in Babina et al., (2024). Columns (6) and (7) replicate the baseline while adding a control for *Top-10 Uni Hiring*, a continuous measure capturing a firm’s exposure to elite universities through its pre-2010 hiring links as in Babina et al. (2024). Columns (8) to (10) repeat the 2SLS specifications with this additional control. Standard errors are clustered at the supplier level and reported in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	<i>Baseline: Supplier, Customer, Year FE</i>		<i>IV 1st Stage</i>	<i>IV 2nd Stage</i>		<i>Baseline: Supplier, Customer, Year FE with Top 10 Uni Hiring as Control</i>		<i>IV 1st Stage</i>	<i>IV 2nd Stage</i>	
	<i>MCS-to-Sales</i>	<i>MCS-to-Assets</i>	<i>AI Intensity</i>	<i>MCS-to-Sales</i>	<i>MCS-to-Assets</i>	<i>MCS-to-Sales</i>	<i>MCS-to-Assets</i>	<i>AI Intensity</i>	<i>MCS-to-Sales</i>	<i>MCS-to-Assets</i>
<i>AI Intensity</i>	0.058*** (0.018)	0.047*** (0.018)				0.056*** (0.018)	0.045** (0.017)			
<i>AI-Strong Uni Hiring</i>			1.477*** (0.206)					1.471*** (0.206)		
<i>Instrumented AI Intensity</i>				0.075** (0.038)	0.125*** (0.041)				0.075** (0.037)	0.125*** (0.040)
<i>ROA</i>	0.009 (0.013)	0.036** (0.014)	0.108*** (0.023)	0.007 (0.008)	0.026*** (0.009)	0.008 (0.013)	0.034** (0.014)	0.105*** (0.023)	0.006 (0.008)	0.025*** (0.008)
<i>Sales Growth</i>	0.001 (0.004)	-0.003 (0.003)	0.030*** (0.011)	0.001 (0.003)	-0.005 (0.003)	0.001 (0.004)	-0.003 (0.003)	0.029*** (0.010)	0.000 (0.003)	-0.006 (0.003)
<i>Firm Size</i>	-0.008*** (0.002)	-0.008*** (0.002)	0.011*** (0.003)	-0.008*** (0.001)	-0.009*** (0.001)	-0.008*** (0.002)	-0.008*** (0.002)	0.010*** (0.003)	-0.008*** (0.001)	-0.009*** (0.001)
<i>Volatility</i>	-0.019 (0.024)	0.009 (0.027)	0.140** (0.061)	-0.021 (0.018)	-0.002 (0.020)	-0.022 (0.024)	0.007 (0.027)	0.134** (0.060)	-0.024 (0.018)	-0.004 (0.020)
<i>Firm Age</i>	0.005 (0.003)	0.009** (0.003)	-0.018*** (0.006)	0.005*** (0.002)	0.010*** (0.002)	0.005 (0.003)	0.008** (0.003)	-0.018*** (0.006)	0.005*** (0.002)	0.010*** (0.002)
<i>SG&A</i>	-0.020 (0.013)	0.024 (0.017)	-0.049* (0.027)	-0.019** (0.008)	0.028*** (0.009)	-0.022* (0.013)	0.022 (0.017)	-0.053** (0.027)	-0.021*** (0.008)	0.026*** (0.009)
<i>R&D</i>	0.050	-0.029	0.884***	0.035	-0.100**	0.048	-0.031	0.876***	0.032	-0.102**

	(0.035)	(0.038)	(0.055)	(0.038)	(0.041)	(0.035)	(0.038)	(0.055)	(0.037)	(0.040)
<i>CAPEX</i>	0.006	-0.037	-0.153**	0.008	-0.025	0.009	-0.034	-0.144**	0.012	-0.022
	(0.033)	(0.024)	(0.067)	(0.020)	(0.022)	(0.033)	(0.024)	(0.067)	(0.020)	(0.022)
<i>Leverage</i>	0.001	0.002	-0.107***	0.003	0.011	0.001	0.002	-0.106***	0.003	0.011
	(0.007)	(0.008)	(0.015)	(0.006)	(0.007)	(0.007)	(0.008)	(0.015)	(0.006)	(0.007)
<i>Dividend</i>	-0.000	0.001	-0.020**	-0.000	0.002	0.000	0.002	-0.019*	0.001	0.003
	(0.005)	(0.007)	(0.010)	(0.003)	(0.003)	(0.005)	(0.007)	(0.010)	(0.003)	(0.003)
<i>Blockholder</i>	-0.001	-0.004	0.007	-0.001	-0.004*	-0.001	-0.004	0.006	-0.001	-0.004*
	(0.003)	(0.004)	(0.008)	(0.002)	(0.003)	(0.003)	(0.004)	(0.008)	(0.002)	(0.003)
<i>Customer Firm Size</i>	0.005***	0.005***	0.003	0.005***	0.005***	0.005***	0.005***	0.003	0.005***	0.005***
	(0.001)	(0.001)	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)	(0.001)	(0.001)
<i>Customer ROA</i>	-0.002	-0.001	-0.000	-0.002	-0.002	-0.003	-0.003	-0.004	-0.003	-0.003
	(0.009)	(0.009)	(0.022)	(0.006)	(0.007)	(0.008)	(0.008)	(0.022)	(0.006)	(0.007)
<i>Customer R&D</i>	0.041	0.030	0.155***	0.039**	0.018	0.042	0.031	0.156***	0.039**	0.018
	(0.048)	(0.031)	(0.057)	(0.018)	(0.019)	(0.049)	(0.032)	(0.057)	(0.017)	(0.019)
<i>Customer Leverage</i>	0.005	0.004	-0.018	0.005	0.005	0.004	0.003	-0.020*	0.004	0.004
	(0.004)	(0.004)	(0.011)	(0.003)	(0.004)	(0.004)	(0.004)	(0.011)	(0.003)	(0.004)
<i>Customer Asset Growth</i>	-0.007*	-0.004	0.025**	-0.007**	-0.006	-0.007	-0.004	0.025**	-0.007**	-0.006
	(0.004)	(0.004)	(0.012)	(0.004)	(0.004)	(0.004)	(0.004)	(0.012)	(0.004)	(0.004)
<i>Customer Return</i>	0.003	-0.000	0.005	0.003*	-0.000	0.003	-0.000	0.005	0.003*	-0.000
	(0.002)	(0.002)	(0.005)	(0.001)	(0.001)	(0.002)	(0.002)	(0.005)	(0.001)	(0.001)
<i>Top-10 Uni Hiring</i>						0.190**	0.172*	0.403***	0.183***	0.140***
						(0.093)	(0.098)	(0.115)	(0.037)	(0.039)
<i>Supplier FE</i>	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
<i>Customer FE</i>	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
<i>Year FE</i>	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
<i>Constant</i>	0.018	0.005	-0.017	0.017*	0.001	0.022	0.009	-0.008	0.021**	0.005
	(0.020)	(0.021)	(0.033)	(0.009)	(0.010)	(0.021)	(0.021)	(0.033)	(0.009)	(0.010)
<i>Observations</i>	3,793	3,793	3,793	3,793	3,793	3,793	3,793	3,793	3,793	3,793
<i>Adjusted R-squared</i>	0.133	0.128	0.262	0.097	0.110	0.141	0.133	0.264	0.107	0.117

Table 8. AI Investment and Sales to Major Customers: Entropy Balancing

This table reports entropy-balancing evidence for the relation between firm AI investment and sales to major customers using the supplier–customer–year panel for 2010–2021. Missing customer sales between the first and last year of a disclosed supplier–customer relationship are set to zero. The relationship window is extended by up to three years after the last reported sale. Panel A reports the means of the supplier characteristics used in the weighting procedure before and after entropy balancing. With AI denotes supplier-years with positive AI Intensity, and Without AI denotes supplier-years with AI Intensity equal to zero. Panel B reports weighted regressions of sales to major customers on firm AI investment using the entropy-balancing weights. The dependent variable in Column (1), *MCS-to-Sales*, is the natural logarithm of one plus supplier sales to a given major customer, scaled by the supplier’s total sales. The dependent variable in Column (2), *MCS-to-Assets*, is the natural logarithm of one plus supplier sales to a given major customer, scaled by the supplier’s total assets. *AI Intensity* is the percentage of a firm’s employees whose resumes list AI-related skills as in Babina et al. (2024). Supplier–customer pair fixed effects and year fixed effects are included. Standard errors are clustered at the supplier level and reported in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively. Detailed variable definitions appear in Table A1.

<i>Panel A. Covariate Balance Before and After Entropy Balancing</i>				
	<i>Before Entropy Balancing</i>		<i>After Entropy Balancing</i>	
	<i>With AI</i>	<i>Without AI</i>	<i>With AI</i>	<i>Without AI</i>
<i>ROA</i>	0.108	0.094	0.108	0.108
<i>Sales Growth</i>	0.078	0.109	0.078	0.078
<i>Firm Size</i>	7.373	6.410	7.373	7.371
<i>Volatility</i>	0.123	0.144	0.123	0.123
<i>Firm Age</i>	2.948	2.889	2.948	2.948
<i>SG&A</i>	0.298	0.255	0.298	0.297
<i>R&D</i>	0.098	0.056	0.098	0.098
<i>CAPEX</i>	0.044	0.064	0.044	0.044
<i>Leverage</i>	0.461	0.464	0.461	0.461
<i>Dividend</i>	0.356	0.302	0.356	0.356
<i>Blockholder</i>	0.571	0.539	0.571	0.571

Panel B. Entropy-Balanced Regressions of Major-Customer Sales

	(1)	(2)
	<i>MCS-to-Sales</i>	<i>MCS-to-Assets</i>
<i>AI Intensity</i>	0.019** (0.009)	0.028** (0.012)
<i>ROA</i>	0.011 (0.013)	-0.019 (0.017)
<i>Sales Growth</i>	0.001 (0.004)	0.001 (0.005)
<i>Firm Size</i>	-0.006 (0.004)	-0.015*** (0.005)
<i>Volatility</i>	-0.022 (0.019)	-0.068*** (0.019)
<i>Firm Age</i>	-0.042*** (0.015)	-0.047*** (0.014)
<i>SG&A</i>	-0.013 (0.020)	-0.021 (0.023)
<i>R&D</i>	0.032 (0.053)	0.033 (0.052)
<i>CAPEX</i>	-0.011 (0.024)	0.013 (0.026)
<i>Leverage</i>	0.001 (0.006)	0.014** (0.007)
<i>Dividend</i>	0.006 (0.005)	0.006 (0.004)
<i>Blockholder</i>	-0.002 (0.003)	0.001 (0.002)
<i>Customer Firm Size</i>	-0.000 (0.003)	0.002 (0.003)
<i>Customer ROA</i>	0.012* (0.007)	0.007 (0.006)
<i>Customer R&D</i>	0.048** (0.020)	0.035 (0.022)
<i>Customer Leverage</i>	-0.000 (0.003)	-0.002 (0.003)
<i>Customer Asset Growth</i>	-0.002 (0.002)	-0.001 (0.002)
<i>Customer Return</i>	0.000 (0.001)	0.001 (0.001)
<i>Supplier-Customer FE</i>	Yes	Yes
<i>Year FE</i>	Yes	Yes
<i>Constant</i>	0.204*** (0.060)	0.265*** (0.067)
<i>Observations</i>	3,902	3,902
<i>Adjusted R-squared</i>	0.717	0.711

Table 9. AI Investment and Technological Linkages with Major Customers

This table reports regressions of supplier–customer technological linkages on firm AI investment using the supplier–customer–year panel for 2010–2021. Missing customer sales between the first and last year of a disclosed supplier–customer relationship are set to zero. The relationship window is extended by up to three years after the last reported sale. The dependent variable in Column (1), *With Supplier Cite Customer*, is an indicator equal to one if the supplier cites at least one patent owned by its major customer in a given year, and zero otherwise. The dependent variable in Column (2), *With Cross Citation*, is an indicator equal to one if there is at least one patent cross-citation between the supplier and its major customer in a given year, and zero otherwise. *AI Intensity* is the percentage of a firm’s employees whose résumés list AI-related skills, following Babina et al. (2024). Supplier–customer pair fixed effects and year fixed effects are included. Standard errors are clustered at the supplier level and reported in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively. Detailed variable definitions appear in Table A1.

<i>Dep. Var.</i>	(1)	(2)
	<i>With Supplier Cite Customer</i>	<i>With Cross Citation</i>
<i>AI Intensity</i>	0.056** (0.026)	0.075*** (0.029)
<i>ROA</i>	-0.026 (0.023)	-0.039 (0.028)
<i>Sales Growth</i>	0.004 (0.004)	-0.004 (0.005)
<i>Firm Size</i>	-0.011 (0.012)	0.003 (0.008)
<i>Volatility</i>	0.032 (0.041)	0.019 (0.052)
<i>Firm Age</i>	0.019 (0.020)	0.003 (0.022)
<i>SG&A</i>	0.010 (0.037)	0.003 (0.036)
<i>R&D</i>	-0.080 (0.118)	-0.050 (0.106)
<i>CAPEX</i>	-0.053 (0.051)	-0.070 (0.078)
<i>Leverage</i>	-0.008 (0.012)	-0.007 (0.018)
<i>Dividend</i>	0.015 (0.014)	0.017 (0.014)
<i>Blockholder</i>	-0.002 (0.006)	0.004 (0.007)
<i>Customer Firm Size</i>	0.007 (0.006)	0.005 (0.008)
<i>Customer ROA</i>	-0.027 (0.023)	-0.036 (0.026)
<i>Customer R&D</i>	-0.181* (0.105)	-0.231** (0.117)
<i>Customer Leverage</i>	0.002 (0.004)	-0.003 (0.005)
<i>Customer Asset Growth</i>	-0.005 (0.003)	-0.002 (0.005)
<i>Customer Return</i>	-0.000 (0.003)	0.006** (0.003)
<i>Supplier-Customer FE</i>	Yes	Yes
<i>Year FE</i>	Yes	Yes
<i>Constant</i>	-0.000 (0.115)	-0.011 (0.103)
<i>Observations</i>	3,902	3,902
<i>Adjusted R-squared</i>	0.553	0.660

Table 10. Heterogeneity by Relationship Embeddedness and Coordination Complexity

This table presents cross-sectional regressions examining whether the positive relation between firm-level AI investment and major-customer sales varies across firm and relationship characteristics, using the supplier–customer–year panel for 2010–2021. Missing customer sales between the first and last year of a disclosed supplier–customer relationship are set to zero, and the relationship window is extended by up to three years after the last reported sale. Panel A examines whether the effect of AI investment is stronger when supplier–customer relationships are more embedded or when suppliers are more dependent on major customers. *Long Duration* equals one if the supplier–customer relationship length exceeds the sample median. *High Customer Concentration* equals one if the supplier’s customer-base concentration, measured as the sum of squared customer sales shares, is above the sample median, following Patatoukas (2012). *Large Market Share* equals one if the supplier’s share of total three-digit SIC industry sales exceeds the annual median. Panel B examines whether the effect of AI investment is stronger when suppliers face greater operational or relational complexity. *High Segment Complexity* equals one if the supplier operates in more than one business segment, defined using four-digit SIC segment classifications. *High Demand Volatility* equals one if the supplier’s rolling standard deviation of quarterly sales growth over the previous 12 quarters is above the sample median. *Different Industry* equals one if the supplier and customer operate in different four-digit SIC industries. The dependent variable in Columns (1) and (3), *MCS-to-Sales*, is the natural logarithm of one plus supplier sales to a given major customer, scaled by the supplier’s total sales. The dependent variable in Columns (2) and (4), *MCS-to-Assets*, is the natural logarithm of one plus supplier sales to a given major customer, scaled by the supplier’s total assets. *AI Intensity* is the percentage of a firm’s employees whose resumes list AI-related skills as in Babina et al., (2024). All regressions include the same set of control variables as in Table 2. Supplier–customer pair fixed effects and year fixed effects are included. Standard errors are clustered at the supplier level and reported in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively. Detailed variable definitions appear in Table A1.

<i>Pane A: Relationship Embeddedness and Economic Incentives</i>						
	(1)	(2)	(3)	(4)	(5)	(6)
	<i>MCS-to-Sales</i>	<i>MCS-to-Assets</i>	<i>MCS-to-Sales</i>	<i>MCS-to-Assets</i>	<i>MCS-to-Sales</i>	<i>MCS-to-Assets</i>
<i>AI Intensity</i>	0.019** (0.009)	0.019** (0.009)	0.020** (0.009)	0.023** (0.010)	0.023** (0.011)	0.024** (0.011)
<i>Long Duration</i>	0.002 (0.003)	-0.002 (0.003)				
<i>AI Intensity</i> × <i>Long Duration</i>	0.016* (0.008)	0.022*** (0.008)				
<i>High Customer Concentration</i>			-0.008*** (0.002)	-0.006* (0.003)		
<i>AI Intensity</i> × <i>High Customer Concentration</i>			0.020** (0.009)	0.019** (0.010)		
<i>Large Market Share</i>					0.017** (0.007)	0.016** (0.008)
<i>AI Intensity</i> × <i>Large Market Share</i>					0.034* (0.018)	0.046** (0.018)
<i>Controls</i>	Yes	Yes	Yes	Yes	Yes	Yes
<i>Supplier-Customer FE</i>	Yes	Yes	Yes	Yes	Yes	Yes
<i>Year FE</i>	Yes	Yes	Yes	Yes	Yes	Yes
<i>Constant</i>	0.194***	0.260***	0.188***	0.246***	0.169***	0.230***

	(0.036)	(0.035)	(0.036)	(0.068)	(0.057)	(0.066)
<i>Observations</i>	3,902	3,902	3,902	3,902	3,902	3,902
<i>Adjusted R-squared</i>	0.690	0.656	0.691	0.657	0.695	0.664
<i>Panel B: Adaptation and Coordination Complexity</i>						
	(1)	(2)	(3)	(4)	(5)	(6)
	<i>MCS-to-Sales</i>	<i>MCS-to-Assets</i>	<i>MCS-to-Sales</i>	<i>MCS-to-Assets</i>	<i>MCS-to-Sales</i>	<i>MCS-to-Assets</i>
<i>AI Intensity</i>	0.028***	0.032***	0.019	0.024***	0.017*	0.028***
	(0.007)	(0.007)	(0.013)	(0.009)	(0.009)	(0.009)
<i>High Segment Complexity</i>	0.001	0.004				
	(0.004)	(0.004)				
<i>AI Intensity × High Segment Complexity</i>	0.017*	0.020**				
	(0.010)	(0.009)				
<i>High Demand Volatility</i>			-0.003	-0.001		
			(0.003)	(0.002)		
<i>AI Intensity × High Demand Volatility</i>			0.020*	0.016**		
			(0.011)	(0.008)		
<i>Different Industry</i>					-0.005	-0.000
					(0.007)	(0.006)
<i>AI Intensity × Different Industry</i>					0.033***	0.017*
					(0.010)	(0.009)
<i>Controls</i>	Yes	Yes	Yes	Yes	Yes	Yes
<i>Supplier-Customer FE</i>	Yes	Yes	Yes	Yes	Yes	Yes
<i>Year FE</i>	Yes	Yes	Yes	Yes	Yes	Yes
<i>Constant</i>	0.156***	0.210***	0.189***	0.245***	0.187***	0.243***
	(0.037)	(0.037)	(0.057)	(0.035)	(0.036)	(0.035)
<i>Observations</i>	3,485	3,485	3,902	3,902	3,902	3,902
<i>Adjusted R-squared</i>	0.734	0.696	0.690	0.656	0.691	0.656

Table 11. AI Investment and Co-movement with Major Customers

This table reports regressions examining the relation between firm-level AI investment and major-customer relationship dynamics using the supplier–customer–year panel for 2010–2021. Columns (1) and (2) examine relationship termination and follow Bauer et al. (2018). The dependent variable, *Termination*, equals one if the supplier–customer relationship is terminated in year $t+1$, and zero otherwise. Column (1) reports an OLS linear probability model, and Column (2) reports a logit model. The sample in Columns (1) and (2) consists of supplier–customer relationships for which relationship termination can be identified from major-customer disclosures. Columns (3) and (4) examine supplier–customer co-movement and are estimated on the subset of supplier–customer–year observations with sufficient data to construct the corresponding co-movement measures. The dependent variable in Column (3), *Partial Correlation*, is the partial correlation between supplier and customer monthly stock returns over a rolling 36-month window, controlling for common exposure to aggregate market returns. The dependent variable in Column (4), *Earnings Correlation*, is the correlation in earnings performance between supplier and customer firms over a rolling 12-quarter window. *AI Intensity* is the percentage of a firm’s employees whose résumés list AI-related skills as in Babina et al., (2024). Supplier–customer pair fixed effects and year fixed effects are included. Standard errors are clustered at the supplier level and reported in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively. Detailed variable definitions appear in Table A1.

Dep. Var.	(1)	(2)	(3)	(4)
	Termination		Partial Correlation	Earnings Correlation
	OLS	Logit		
<i>AI Intensity</i>	-0.188** (0.091)	-0.650*** (0.249)	0.067** (0.029)	0.088* (0.053)
<i>ROA</i>	0.130 (0.110)	-0.103 (0.332)	0.007 (0.026)	0.031 (0.061)
<i>Sales Growth</i>	0.008 (0.034)	0.073 (0.109)	-0.014* (0.008)	-0.004 (0.018)
<i>Firm Size</i>	-0.051 (0.044)	-0.021 (0.048)	0.001 (0.011)	0.006 (0.029)
<i>Volatility</i>	0.011 (0.200)	0.806 (0.762)	-0.031 (0.065)	-0.109 (0.133)
<i>Firm Age</i>	0.597*** (0.117)	-0.138 (0.089)	0.028 (0.047)	-0.120 (0.087)
<i>SG&A</i>	0.200 (0.219)	0.546 (0.401)	-0.076 (0.056)	0.180* (0.106)
<i>R&D</i>	-0.237 (0.435)	-0.371 (0.906)	0.193* (0.109)	-0.210 (0.246)
<i>CAPEX</i>	0.112 (0.281)	0.549 (0.934)	0.072 (0.086)	-0.196 (0.171)
<i>Leverage</i>	-0.024 (0.067)	0.088 (0.225)	0.013 (0.019)	0.012 (0.037)
<i>Dividend</i>	-0.083 (0.051)	-0.294** (0.149)	-0.000 (0.017)	0.020 (0.039)
<i>Blockholder</i>	-0.003 (0.027)	-0.135 (0.118)	-0.002 (0.009)	0.026 (0.019)
<i>Customer Firm Size</i>	0.035 (0.038)	-0.056** (0.028)	-0.025 (0.016)	0.016 (0.023)
<i>Customer ROA</i>	-0.099 (0.132)	-0.110 (0.311)	0.082** (0.036)	-0.020 (0.062)
<i>Customer R&D</i>	0.034 (0.346)	0.222 (0.823)	-0.088 (0.116)	0.146 (0.188)
<i>Customer Leverage</i>	-0.065 (0.070)	-0.352* (0.209)	0.005 (0.013)	-0.002 (0.031)
<i>Customer Asset Growth</i>	0.035 (0.053)	0.112 (0.143)	-0.019* (0.012)	-0.009 (0.022)
<i>Customer Return</i>	0.001 (0.015)	0.027 (0.061)	-0.002 (0.004)	0.007 (0.010)
<i>Supplier-Customer FE</i>	Yes	No	Yes	Yes
<i>Year FE</i>	Yes	Yes	Yes	Yes
<i>Industry FE</i>	Yes	Yes	Yes	Yes

<i>Constant</i>	-1.573*** (0.522)	1.054 (0.957)	0.236 (0.194)	0.181 (0.330)
<i>Observations</i>	2,036	2,443	3,584	3,762
<i>Adjusted/Pseudo R-squared</i>	0.132	0.065	0.677	0.299
