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Abstract

We investigate the role of private equity (PE) investors as an intermediary to digital technology adoption in private firms. Using a unique dataset of digital technology investment in private companies, we examine digital investments in PE portfolio companies and find a significant increase, post PE investment, in investments in new digital technologies. This effect is more pronounced for firms that we expect will be impacted by technological advancements, and for firms with PE investors with greater expertise in digital technologies. The adoption of digital technologies is related to better portfolio company growth. Next, we examine whether PE investors respond to technological shocks by reallocating capital towards firms that potentially stand to benefit more from digital technologies. Using an exogenous innovation in artificial intelligence (AI), the development of AlexNet, we find that PE investors (i) shift their target investments to firms that are likely to be impacted by AI and (ii) increase their existing portfolio firms' digital technology investments. Overall, we highlight the role of PE investors as an important intermediary for enhancing private firm technology adoption.

Keywords: Digital technologies; private equity; IT investment; artificial intelligence; technology

JEL Codes: G24; G32; O33

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1. Introduction

Technological change is a key driver of firm performance and economic growth (Romer, 1990; Aghion & Howitt, 1992; Kogan et al., 2017). Yet, realizing the benefits of digital technologies requires firms to overcome significant barriers to adoption (Bresnahan and Greenstein, 1996), including the ability to invest in, integrate, and manage digital infrastructure effectively (Hall & Khan, 2003; Aral & Weill, 2007). While large public firms often lead in digital capability building (Tambe et al., 2020), adoption of advanced technologies remains uneven across the economy—especially among small and private firms (Tambe & Hitt, 2012; Zolas et al., 2020). These disparities reflect not only resource constraints, but also organizational and managerial frictions that inhibit the development of digital capabilities (Brynjolfsson & Hitt, 2000).

In this paper, we examine whether private equity (PE) investors act as intermediaries that accelerate digital transformation in private firms. PE investors typically acquire controlling stakes in private companies and exert strategic influence through board representation, performance monitoring, and operational support. By reshaping governance structures and providing both capital and expertise, PE investors may help overcome barriers that otherwise constrain technology adoption in under-digitized firms. We ask two questions: (i) Does PE ownership lead to increased digital investment in portfolio firms? (ii) Do PE investors respond to major technological shifts—such as breakthroughs in artificial intelligence (AI)—by reallocating capital toward firms and industries more likely to benefit from digital transformation?

Our setting focuses on the PE transactions in the United States between 2010 and 2021. We combine data on PE transactions with two firm-level datasets capturing different dimensions of digital investment: (i) job postings for digital roles (BurningGlass) and (ii) information technology (IT) budgets (Aberdeen). We link these to firm financial data (Dun & Bradstreet) and construct a portfolio firm-year panel. Our empirical strategy uses a stacked difference-in-differences design, comparing PE-backed firms to propensity-score matched controls from the same industry with similar sales, employment, and digital investment at the time of the transaction.

We document a statistically and economically significant increase in digital investment following PE acquisition. On average, PE ownership is associated with a 1.5 percentage point increase in the share of job postings for digital talent (15% relative to the sample mean) and a 20.5% increase in IT budgets (equivalent to $2.64 million) of portfolio companies, compared to private firms with no PE backing. These effects persist across specifications and are not preceded by pre-trends. Moreover, these findings are consistent with the view that PE investors act as governance agents who allocate capital and strategic attention to IT, driving digital transformation in firms that may otherwise lack the capacity to undertake it.

We next examine how these effects vary across firm and investor characteristics. First, we find that increases in IT budgets are concentrated among firms with below-median pre-deal IT-to-sales ratios. This pattern suggests that PE investors selectively target firms that are lagging in information technology investments—those where marginal returns to digital investment are likely to be higher—and deploy capital to address those gaps. Second, we find the effects strengthen in industries with high exposure to AI, based on a measure developed by Felten et al. (2021) that aggregates occupational task-level AI suitability to the industry level. PE-backed firms in high-AI salient industries show greater increases in both digital hiring and IT budgets, consistent with PE investors responding to digital opportunities at the sector level. Additionally, while the effects are somewhat larger for IT firms, the main results hold for non-IT firms as well, alleviating concerns that the findings are driven solely by tech-intensive sectors. Finally, we find slightly stronger effects for growth equity deals relative to buyouts, consistent with the idea that growth-oriented investments focus more on business expansion and capability building.

Third, we analyze investor heterogeneity. We show that PE investors with prior experience on the boards of IT companies are more likely to expand digital investment in their portfolio firms. This effect strengthens with the increase in the number of board members with relevant experience, consistent with prior evidence that investor expertise drives operational value creation (Bernstein & Sheen, 2016). The results suggest that investor capabilities, in addition to firm needs, shape the scope and depth of digital transformation under PE ownership.

Next, we examine the consequences of the digital transformation in two ways. First, prior evidence suggests that the adoption and integration of digital technologies is associated with enhanced productivity and development of new products/services (Babina et al., 2024). We test and find that portfolio firms with a greater increase in digital investments post PE entry achieve faster sales and employee growth, if the PE entry is associated with higher digital job postings or IT budgets. Second, we test whether digital investments are associated with firm innovation. Prior research argues that advanced digital technologies could have an impact on innovation by improving the R&D process (Cockburn et al., 2018). Similar to the growth test discussed above, we analyze and find that increases in machine learning job postings post PE investment are associated with stronger likelihood of obtaining a patent, and with an increase in the number of patents. On the other hand, we do not observe meaningful effects for the IT budget. One reconciliation of the result is that the machine learning job postings capture innovation-related investments more directly than IT budgets, as IT budgets include various aspects into digital investments that may serve other purposes than enhancing innovation efficiency.

We then explore whether technological breakthroughs influence PE investors' capital allocation. We use the introduction of AlexNet in 2012 as a plausibly exogenous shock that marked a turning point in the capabilities and commercial viability of AI technologies (LeCun et al., 2015; Krizhevsky et al., 2017). Using industry-level deal data, we find that the number of PE investments in AI-salient industries increases by 19.1% after 2012. This shift is not observed in low-AI salient industries and is robust to the inclusion of industry and year fixed effects. At the firm level, we also find that digital and machine learning-related hiring increases more for existing portfolio firms with high AI exposure post-AlexNet. Taken together, our results suggest that PE investors act as strategic capital allocators who reorient their investment strategies in response to technological change. Importantly, the association between PE ownership and digital investment strengthens after AlexNet, particularly when board members have prior IT experience, indicating that both capital reallocation and operational transformation are shaped by external technological developments.

We contribute to several strands of academic literature. First, we extend research on IT governance, strategic control, and digital investment by introducing PE investors as external governance agents who shape firms' technology strategies (Aral & Weill, 2007; Benaroch & Chernobai, 2017; Sambamurthy & Zmud, 1999; Weill & Ross, 2004). Prior work has emphasized internal decision rights and managerial alignment in IT resource allocation; we show that PE investors, through ownership concentration and board representation, directly influence digital investment decisions, expanding the scope of governance mechanisms considered in IS research.

Second, we contribute to the literature on the economics of IT by linking digital investment to growth and innovation outcomes in private firms, where performance data are typically unavailable (Bharadwaj, 2000; Brynjolfsson & Hitt, 1996; Brynjolfsson & Hitt, 2000; Chen & Srinivasan, 2024; Dewan & Ren, 2011; Melville et al., 2004; Mithas et al., 2012; Mithas & Rust, 2016). While most studies focus on public firms or financial market reactions, we document real outcomes—sales, employment, and patents—following digital investment in PE-backed firms, thus broadening the settings and outcome domains used to assess IT value. An exception is Kohli et al., (2012), who measure the perceived value of IT investment in private hospitals. Our study adds to theirs as we focus on a broader range of private firms.

Third, we build on the literature on the real effects of private equity ownership by showing that PE investors enhance digital capabilities in portfolio firms, particularly those with initially low IT intensity (Bernstein & Sheen, 2016; Boucly et al., 2011; Cohn et al., 2014, 2022; Davis et al., 2014; Guo et al., 2011; Lerner et al., 2011; see Sorensen & Yasuda, 2023 for a review). This identifies digital transformation as an operational channel through which PE creates value.

Finally, we contribute to the literature on the determinants of PE investment (Baik et al., 2025; Opler & Titman, 1993; Stafford, 2022) by showing that technological change influences capital allocation. Following the introduction of AlexNet, PE investors increase investment in AI-salient industries and expand digital hiring in affected portfolio firms. These findings extend IS theories of sensing and seizing (Sambamurthy et al., 2003) to investor decision-making, highlighting how capital providers reallocate resources in response to technological breakthroughs.

Our study is closely related to Agrawal and Tambe (2016), who find that PE-backed firms enhance employees' IT-related human capital following buyouts. We extend their work in two directions. First, we shift the focus from individual employees to firm-level digital investments, capturing broader organizational transformation. Second, we examine how PE investors respond to technological change by reallocating capital across sectors—highlighting their role as strategic intermediaries who shape not just operational execution, but also the direction of investment in response to emerging technologies.

2. Related literature and hypothesis development

2.1 PE investor's influence on company performance and investments

PE investors are increasingly recognized not only as capital providers but also as strategic agents who actively reshape firm operations, governance, and investment priorities. Unlike public equity investors, PE firms typically take concentrated ownership positions, install their own board members, and exert significant control over managerial decisions (Kaplan & Strömberg, 2009; Gompers et al., 2016). These interventions often involve systematic governance restructuring—smaller and more engaged boards, enhanced performance monitoring, and increased CEO turnover, designed to strengthen accountability and strategic execution (Acharya et al., 2009).

There are two core mechanisms through which PE ownership may influence digital technology investment. First, PE investors restructure governance in ways that enhance the firm's IT decision rights, accountability systems, and resource allocation processes. The IT governance literature emphasizes the importance of formal structures, such as centralized decision authority, strategic IT oversight, and performance-based controls, in aligning technology investment with business strategy (Weill & Ross, 2004; Sambamurthy & Zmud, 1999). By taking control, PE investors install board representatives or operating partners with decision-making authority over major investments, including IT and digital initiatives (e.g., Cornelli and Karakas, 2008; Kaplan & Strömberg, 2009). These governance changes reduce coordination frictions common in dispersed ownership settings and enable disciplined execution of transformation agendas—particularly those involving digital infrastructure and analytics. In this view, PE investors act as centralized IT governance agents, streamlining and professionalizing how technology decisions are made and implemented.

Second, the resource-based view of IT posits that IT generates value only when complemented by organizational capabilities, such as strategic alignment, managerial know-how, and changes in management routines (Bharadwaj, 2000; Melville et al., 2004; Mithas & Rust, 2016; Wade & Hulland, 2004). Many PE firms now bring such capabilities in-house, through dedicated digital operating partners, portfolio support teams, or external consultants focused on value creation through technology (West Monroe, 2019; EY, 2023). These professionals possess deep expertise in areas like automation, customer analytics, and enterprise software, enabling them to identify digital opportunities and drive implementation across their portfolio. In contrast to internal managers, who may lack the strategic vision or technical acumen, PE investors inject external knowledge and cross-firm learning that shapes both whether and how digital investments are made. Moreover, the past experience of these PE investors, may play a role in helping portfolio firms navigate integration issues in digital technology adoption, such as legacy systems (Cao & Iansiti, 2022), co-invention costs (Bresnahan & Greenstein, 1996) and diseconomies of scope (Bresnahan et al, 2012). Overall, this expertise should therefore enhance the firm's absorptive capacity, enabling more effective deployment of digital technologies. These mechanisms, in turn, suggest that PE ownership, via governance transformation and technology expertise, can serve as a catalyst for digital investment in portfolio firms.

Despite these mechanisms, it is not obvious that PE ownership will uniformly increase digital investment for two reasons. First, PE firms are often associated with cost-cutting and financial discipline (Jensen, 1989), which may discourage long-horizon or uncertain IT investments. Notably, prior research on the adoption of IT showed long lags in the productivity benefits of IT adoption (Brynjolfsson and Hitt, 2000), leading to limited impact of these technologies on productivity statistics. Similarly, Kohli et al., 2012 argue that IT investment does not significantly affect firm profitability, although they find positive impact on firm value. Digital technologies and more recent AI technologies, likely share the same features (Brynjolfsson et al, 2017), owing to the fact that these technologies are general purpose and also exhibit long development lags. Specifically, these technologies give rise to new applications and productions, but integrating and refining these technologies take time, and exhibit significant frictions when first introduced (Brynjolfsson and Smith, 2000). Second, digital transformation also requires organizational change and upfront costs that may not align with PE investors' typical holding periods (Lerner et al., 2011). Thus, we argue that PE ownership could just as plausibly lead to underinvestment in IT—especially when the value of digital tools is unclear or investors lack relevant expertise. This tension motivates our examination of contextual factors that shape whether PE facilitates digital investment.

2.2 Advances in technology and PE investor capital reallocation

Recent research in information systems emphasizes that firms—and, by extension, investors—must sense and respond to technological change to remain competitive

(Sambamurthy et al., 2003). This perspective on strategic agility suggests that PE investors may adjust not only the operations of portfolio firms but also their capital allocation strategies across industries and opportunities. Consistent with this view, Ewens et al., (2018) show that VC investors adapt their investing approach following a major technological advancement. In response to major technological breakthroughs, PE investors may reallocate capital toward industries with greater potential for digital transformation. This form of external responsiveness parallels the internal dynamic capabilities that firms use to adapt to technological shifts and reflects a broader portfolio-level approach to enabling digital change.

However, PE investors (especially LBOs) are traditionally thought to focus on industries or firms with a stable and predictive stream of cash flows (Opler & Titman, 1993; Stafford, 2022), which are industries less sensitive to technological changes. If this view continues to prevail in the recent data, PE investors may not change their investment behavior in response to technological changes. This is because firms that engage with technological changes, typically exhibit uncertain cash flows and growth prospects (Pastor and Veronesi, 2004), leading to instability in their valuations.

Based on these conceptual discussions, we formulate and test the following hypothesis:

H1: PE investment in portfolio firms is associated with increases in digital technologies investments.

H2: PE investors adjust to technological advances by changing the types of firms they typically invest in.

3. Data sources

We use multiple sources of data to explore our research questions. We first obtain a sample of PE transactions completed from 2010 to 2021 for firms located in the United States, from Capital IQ, Pitchbook, and Preqin and identify 80,220 PE transactions. We obtain these transactions from multiple sources because each of the datasets do not capture a complete list of PE transactions (Brown et al., 2015). By combining deal information from these three datasets, we are able to identify as many transactions as possible to reduce selection concerns after the matching process. From these datasets, we focus on leveraged buyouts and growth equity transactions.[1] We remove any overlapping PE transactions among these datasets.

To obtain information on hiring demand related to digital technology, we gather information from BurningGlass, a dataset that records job postings. This dataset covers the near-universe of online job postings and has been used to measure corporate job postings on software and digital-related technologies (Babina et al 2024, Acemoglu et al., 2022). To measure digital-specific skills, we use the cluster classification in this dataset to measure a group of skills that relate to machine-learning and related digital technologies, consistent with Goldfarb et al., (2021).

The third dataset we exploit (specifically for PE entry tests) is the Aberdeen data. This data provides detailed information on the amounts of IT expenditures, and various categories of IT and cloud technologies that organizations have invested in. We match this data to our main dataset using the D&B identifier.

4. PE entry and portfolio firm digital investments

4.1 Sample creation and descriptive statistics

[1] Capital IQ has more detailed transaction descriptions. We select "leveraged buyout," "management buyout," "going private," or "growth equity" transactions to identify PE deals.

To construct the main sample to explore whether PE investments are related to increased investments in digital technology, we match the portfolio firms to the D&B data, using (1) website URLs and (2) fuzzy name matching algorithm. D&B is especially useful as it enables us to obtain basic financial information of private firms in the US. We also require sales and employee data to be populated at the year of PE transaction. This procedure yields 15,990 transactions.[2] Using this sample, we separately match Aberdeen and BurningGlass data to preserve as many portcos as possible. Matching the above sample with Aberdeen data (that contains IT budget information), and performing nearest-neighbor matching within the same 2-digit SIC industry yields 12,601 transactions.[3] On the other hand, matching BurningGlass using the same procedure provides 6,466 transactions.

Table 1 shows the summary statistics of our samples. Panel A describes the deal and portfolio firm types of our sample. The composition of deal types is similar between the two samples; the Aberdeen sample has 7,129 and 5,471 growth equity and buyout deals, respectively, while the BurningGlass sample consists of 3,935 and 2,496 growth equity and buyout deals, respectively. In terms of portfolio firm characteristics, the Aberdeen sample consists of 9,466 non-IT firms and 3,134 IT firms; the BurningGlass sample has 4,548 and 1,853 non-IT firms and IT firms, respectively.

Panel B (Panel C) presents the descriptive statistics of the Aberdeen (BurningGlass) sample. We observe that the Aberdeen sample contains larger portfolio firms than those of the BurningGlass sample, with 188.89 (145.09) mean number of employees and $33.41 million ($23.77 million) in sales. Firms in the BurningGlass sample show a higher sales growth (0.21)

[2] Specifically, there are 37,510 deals that have a matching D&B identifier. The deals drop to 24,109 deals when we condition our sample to have at least one year of data during 2010-2021. Finally, we arrive at 15,990 deals when we require firms to have firm data at the year of PE transaction.
[3] To be more specific, we weight the words in each *BurningGlass* organization name and *D&B* company name using TF-IDF and then apply the k-nearest neighbor algorithm for *BurningGlass*/*D&B* companies in the same 2-digit SIC industry. We then select the *BurningGlass* firm with the closest name for each *D&B* firm.

than the firms in the Aberdeen Sample (0.08). In the Aberdeen sample, the mean IT budget is $12.88 million, which is comparable to the statistic reported in He et al., (2022), who report a mean of $11.125 million. In the BurningGlass sample, the mean number of digital job postings is 27.71, which is about 7.7% of the total job postings (mean 360.41).

4.2 Research design

4.2.1 Dependent Variables

Using various databases mentioned above, we employ the following variables as dependent variables. First, we measure the natural log of the dollar amount invested in IT technology, from Aberdeen, which captures the total IT expenditures in each year (following He et al., 2022 and Charoenwong et al., 2024). Second, we study the proportion of digital job postings relative to total job postings, pre and post PE investment.[4] Specifically, we classify a job posting to be digital-related if the posting lists skills that are part of one of these skill clusters identified by BurningGlass: machine learning, data science, natural language processing, data mining, big data, business intelligence (BI), and cloud. We examine these postings using the proportion of digital job postings relative to total job postings as the dependent variable.

4.2.2 Differences-in-differences

One of the most important research design-related concerns in our setting is that it is extremely difficult to rule out endogeneity. First, firms that receive PE investment may be inherently different from the ones that do not receive funding from PE investors. For instance, portfolio firms may be firms that would be effective if the PE investors invested in digital technologies. Second, there is an endogeneity concern that PE investors may time the transaction period correctly, selecting firms that are about to make large digital investments, and IT

[4] We follow prior literature to measure the demand for AI technologies using job posting data (i.e. Alekseeva et al., 2021; Acemoglu et al., 2022).

investment would have surged regardless of PE investment. These concerns are especially difficult to address in the US setting, where financial statements of private firms are unavailable.

To attenuate these concerns, we employ a stacked differences-in-differences strategy to conduct our analyses. To do so, we carefully select a group of control firms that have similar firm characteristics and industries via propensity score matching, which is obtained from D&B. The firms are required to be in the same industry (SIC two-digit code) and have similar sales and employees measured at one year before the treated firm's PE transaction. The covariate balance of the treated and control samples are reported in Table IA1 in the Internet Appendix.[5] By selecting a group of control firms with similar firm characteristics, we are able to reduce the concerns mentioned above. We remove firm-years that are after two years post PE deal, as we expect the effects to be most concentrated in the years right after the PE deal.

Using the sample of treated and control firms, we implement the following baseline regression:

$$Y_{i,t} = \beta_1 Treat_i \, x \, Post_i + \gamma X' + \alpha_i + \alpha_t + \varepsilon_{i,t} \quad (1)$$

Where the dependent variables are different measures of digital investments; $Treat_i$ equals one if the firm had received investment from a PE firm (treated) in our sample period, and zero otherwise; $Post_t$ equals one for the firm-years after the treated firm is acquired by the PE Firm, and zero otherwise. $\gamma X'$ represents a vector of additional controls, namely, natural log of sales and employees, and sales growth, to capture firm size and firm growth. To further control

[5] Table IA1 in the Internet Appendix reports the covariate balance between the treated and control groups, at the year of the treated firm's PE transaction. Panel A (B) reports the balance in the *Aberdeen* (*BurningGlass*) sample. In the *Aberdeen* sample, we find no statistical difference in the number of employees between the treated and control firms but find a difference in terms of the natural log of sales (0.7). However, when transformed into dollar terms, the difference in sales is approximately $615,000, which we argue is a small number. In the BurningGlass sample, we find no statistical difference in terms of sales and employees between treated and control groups.

for across firm heterogeneity and time-trends, we also include α_i and α_t as firm and matched-pair year fixed effects, respectively. By including firm fixed effects, we address time-invariant selection issues in PE investment, and by including matched-pair year fixed effects we mitigate the biases induced in staggered different-in-difference designs (Baker et al., 2022).

4.3 Main results

We first graphically analyze whether there is a significant increase in digital investments post PE transactions. Figure 3, Panel A presents the levels of IT budgets pre and post PE transactions, for treated and control firms, that have information available across the entire event period (i.e., two years before and two years after the PE transaction). Purple (yellow) line represents treated (control) firms. Consistent with our prediction, we observe similar patterns into IT investment before PE transactions for both types of firms; once the PE invests in the treated firm, we find a sharp increase in treated IT budgets from year *t+1*. The limited differences in pre-trends provides some validation to our matching approach.

Figure 3 Panel B plots the levels of digital job posting proportions for treated and control firms instead. Again, this panel presents the mean values for the sample of treated and control firms that contain information across the entire event period. Purple (yellow) line represents treated (control) firms. Consistent with our predictions, we find an increase in the proportion of digital job postings from *t+1*. Overall, the figures support our prediction that PE transactions are related to higher investment in digital technologies. Like our analysis in Panel A of this table, we also show that there are limited differences in pre-trends before the PE investment year.

Table 2 presents the results for our main regression model outlined in Equation (1). Panel A presents the main results, where dependent variables are the proportion of digital job postings and the natural log of IT budget, in columns (1), (2) and (3), (4), respectively. Consistent with our hypothesis, we find a significant increase in digital investments across both approaches post PE investment, compared to the control group. Economically, PE investment is related to 1.5% point increase (which is 15% relative to the unconditional mean) in proportion of digital job postings and 20.5% increase (approximately a \$2.64 million increase) in IT investments.

Panel B estimates the dynamic effects of the main regression results to ensure that there are no observed pre-trends. Consistent with the results in Panel A, we find significant coefficients for variables $Treat_i \times Post_{i,t=1}$ and $Treat_i \times Post_{i,t=2}$. On the other hand, the coefficients $Treat_i \times Pre_{i,t=-1}$ and $Treat_i \times Pre_{i,t=-2}$ are not statistically significant, which suggests that there are no observable pre-trends with our results and ultimately, reduces the concern that other unobservable characteristics are driving our main results. Overall, the main regression results are consistent with our main hypothesis that PE investment is associated with increased digital investments of the portfolio firms.

4.4 Cross-sectional results - portfolio firm/transaction characteristics

4.4.1 Extensive versus intensive margins

To deepen our understanding of the mechanism, we examine whether PE-driven increases in IT budgets are concentrated among firms with initially low IT investment. This test is grounded in research showing that the marginal returns to IT are higher when baseline investment is low, especially in the presence of governance that enables alignment and execution (Melville et al., 2004; Bharadwaj, 2000). A low IT-to-sales ratio may signal untapped digital potential that internal managers fail to address.

Table 3 presents the results testing this idea. Specifically, we split the sample based on whether a firm's pre-buyout IT-to-sales ratio is above or below the industry-year median. We then estimate the treatment effect separately for each group to test whether the observed increase in IT budgets is driven primarily by firms with below-median pre-investment IT intensity. In Panel A of Table 3, our analysis shows that the effect of PE ownership on IT budgets is strongly concentrated in firms that were below the median IT-to-sales ratio prior to investment. Specifically, the increase in IT budget is statistically and economically significant for this group, while the effect is muted and statistically insignificant for firms with high IT investment prior to PE ownership. In Panel B of Table 3, we compare the coefficient on the effect of PE ownership on IT budget across the two samples, and we further show that the coefficient is stronger in the sub-sample of firms with below median IT-to-sales before PE investment. This pattern is consistent with the view that PE investors identify digital underinvestment as a value-creation opportunity and actively deploy capital to correct these inefficiencies. It also mitigates concerns that the main effect is mechanical—i.e., that PE investors are simply scaling up already digitized businesses and investing in IT budgets to maintain existing digital infrastructure.

This result complements our main analysis in two ways. First, it reinforces the interpretation of PE investors as selective and strategic IT allocators, rather than passive allocators of IT spending. Second, it aligns with existing IS theory that highlights the importance of IT investment alignment and marginal returns: firms that are underinvested in IT relative to peers are more likely to benefit from disciplined governance and capital infusion (Bharadwaj, 2000; Melville et al., 2004). The fact that PE ownership catalyzes IT investment primarily in firms with room to grow suggests that investors are not simply reacting to secular digital trends but are deliberately deploying capital where IT may have a larger impact.

Taken together, this heterogeneity results strengthens our interpretation that PE ownership enables targeted digital transformation. Rather than a uniform push toward technology, PE firms appear to act as adaptive IT governance agents, selectively scaling digital infrastructure where it is most needed and potentially most productive.

4.4.2 AI suitability

To assess whether PE investors selectively target firms where digital transformation opportunities are greatest, we examine heterogeneity in treatment effects based on industry-level AI exposure, using the measure developed by Felten et al. (2021). This measure captures the suitability of AI technologies for performing tasks within an industry, based on a two-step approach: first, expert surveys assess the feasibility of automating specific occupational tasks with AI; then, these task-level scores are aggregated to occupations and mapped to industries using employment data from the U.S. Bureau of Labor Statistics. The resulting metric reflects the potential of AI to replace tasks performed by the occupations of the industries. For instance, professional services, such as accounting and bookkeeping are classified as an industry with high AI suitability; on the other hand, construction-related industries are defined as a low AI suitability industry. We classify industries as high or low AI suitability based on whether their Felten score is above or below the sample median (defined as "high AIIE" or "low AIIE"). If PE investors are responsive to technological frontier shifts, we would expect greater increases in IT budgets and digital hiring in portfolio firms operating in high AI-suitability industries.

Table 4 presents evidence exploiting cross-sectional variation at the portfolio firm-level. First, we test whether portfolio firms in industries with high AI suitability ("high AIIE") are related to greater digital investments post PE investment, i.e., industries that are more likely to be affected by developments in AI. In Panel A columns (1) and (2), we regress the proportion of digital job postings and IT budget on the triple interaction term, $Treat\ x\ Post\ x\ High\ AIIE$ (as well as the main effects and controls). The results indicate that industries/portcos with high AI suitability show stronger measures of digital investment post PE investment, consistent with our expectations. Specifically, we find a greater increase in both digital postings and IT budgets for high AIIE industries, while we only find a statistically significant increase in IT budgets in low AIIE industries (but not for digital job postings). Thus, the overall evidence supports our prediction that PE investors invest more in digital technologies where the opportunity is the greatest.

4.4.3 Non-IT/IT firms

We also assess whether our main findings are different between non-IT and IT portfolio firms. While we anticipate that the magnitude of increase would be higher for portfolio firms in the IT industry, we expect the increase to still exist in the non-IT portfolio firms, as prior work documents the benefits of digital transformation in the non-IT industry (Babina et al., 2024; Chen and Srinivasan, 2023). To test this claim, similar to the cross-sectional tests mentioned above, we interact IT_d to the main variable $Treat_i \times Post_{i,t}$, where IT_d equals one if the portfolio firm is in the IT industry, and zero otherwise.

Table 4 Panel B presents the results for the above test. For both dependent variables, while we observe slightly stronger effects for IT portcos for both columns, the main effect $Treat_i \times Post_t$ is still statistically significant, which is consistent with our conjecture that non-IT firms also increase digital investments post PE deal. This reduces the concern that our results are entirely driven by IT portcos.

4.4.4 Buyout/growth equity investments

In terms of deal characteristics, we classify PE deals into buyout and growth equity transactions and assess which types of PE deals exhibit greater growth. Buyout deals involve PE investors acquiring a majority stake and these PE investors typically exert a much stronger control over their investments. Furthermore, these types of investments are associated with maintaining cash flow profitability, because of the need to pay interest on the high amount of leverage the portfolio firms take to complete the PE transaction. Consistent with this notion, Jensen (1989) argues that buyouts are an ideal organizational form, as leverage 'disciplines' the firms to make prudent decisions and cut costs. On the other hand, growth equity deals are transactions where the PE investors generally invest a minority stake in the portfolio firm. Unlike buyout transactions, growth equity investors are more willing to focus on the portfolio firm's growth than maintaining profitability. To test the differences between growth equity and buyout deals, we add an indicator variable $Growth_d$ as a triple interaction, which equals one if the portfolio firm received a growth equity deal, and zero otherwise.

Table 4 Panel C presents the results on this test. We find that the increase in IT budgets is stronger for growth equity transactions than for buyouts, while we observe no meaningful incremental difference in digital job postings. While there is some evidence that growth equity portcos show stronger increases, the fact that the results hold for buyout portcos is consistent with the results presented in Agrawal and Tambe (2016). An interpretation of our results is that investments into digital technology can be valuable even for portfolio firms that are focused on cost cutting and stable cash flows, namely buyout investments.

4.5 Cross-sectional results - PE investor technology expertise

Further exploiting investor-level variation, we test whether the results are stronger for deals where the PE investor has experience or expertise investing in technology firms. Our prediction is that PE investors with experience investing in the technology industry would be more aggressive in investing in digital technologies to their portfolio firms, as Bernstein and Sheen (2016) find that PE investor experience shapes the post-investment behavior of the portfolio firms. To test this potential mechanism for our findings, we examine whether the board members' IT expertise is a key driver of our main results. Our motivation for using this proxy for measuring PE investor experience in digital technologies stems from the notion that the board members from the PE investor are the individuals who influence and communicate with the portfolio firm management the most (Acharya et al., 2009). Therefore, it is plausible that the board member's past experience in IT could have a more direct impact on the portfolio firm's digital investment decisions.

Table 5 tests this idea, by regressing the dependent variables on the three-way interaction variable: $Treat\ x\ Post\ x\ PortCo\ Digital\ Board$. In Panel A, we define $PortCo\ Digital\ Board$ equals one if the board member from the PE investor has sat on a board of an IT company, and zero otherwise, which we obtain from *Pitchbook*. In Panel B, we define$PortCo\ Digital\ Board$ as the number of PE board members that sat on IT company boards. Across both panels and dependent variables, we find that the results are significantly stronger for firms with PE board members having experience in sitting on IT company boards. Thus, these results demonstrate that PE investors' previous experience, particularly IT-related, shapes their post-investment behavior (digital spending and hiring), consistent with Bernstein and Sheen (2016).

4.6 Consequences of digital investments

Our results so far indicate that PE investments are associated with different measures of digital investments, and PE investors react to advances in technology. A natural question that may arise is the consequences of digital technology adoption to portfolio firms. To answer this question, we study whether increases in digital technology are associated with performance improvements. In Table 6, we test whether the investments that experienced greater increases in digital transformation are associated with greater sales and employee growth (Panel A) or innovation (Panel B). As the benefits of digital technologies are likely slow-moving (Brynjolfsson and Hitt, 2000), we adapt the regression framework in Babina et al., (2024) and implement a cross-sectional long-difference regression analysis. Specifically, we regress sales/employee/patent growth of the portfolio firms, from one year before PE investment to two years after the PE investment (which is then annualized) relative to the changes in the matched control firm, on the changes in the digital investments (digital job postings and IT budget) in the same period relative to the changes in digital investments in the matched control firm.

In Panel A, our analysis suggests that the increase in digital investment is associated with increases in future firm growth. Specifically, we find a positive association of increases in IT budget with sales and employee growth (columns (3) and (4)), and a weaker relationship between increase in digital job postings and employee growth (column (2)). Conversely, in Panel B, we find that while the increase in digital hiring is positively associated with increased patents (columns (1) and (2)), we do not find any significant association between IT budgets and innovation. We interpret this result consistent with findings in Babina et al., (2024), who show that adoption of digital technologies is associated with enhanced productivity and development of new products and services. In particular, we conjecture that hiring personnel with machine learning expertise may be more relevant for innovation, while increasing IT related budgets could be related to increased productivity and firm growth (Cockburn et al., 2019).

5. Technological shocks and PE investment behavior

5.1 Introduction of AlexNet

To investigate our second research question, we assess whether PE investors respond to breakthrough developments in technology. To be specific, we analyze whether the PE investors are more likely to target firms that are more likely to benefit from AI after an event which triggered a substantial development in the field of AI. We perform this test by using the introduction of AlexNet as a research setting. AlexNet, a convolutional neural network, was introduced in 2012, and this algorithm significantly reduced the error rates of visual recognition and advanced the field of deep learning (LeCun et al., 2015; Krizhevsky et al., 2017). With the introduction of AlexNet (which is a shock to AI's technological development), our prediction is that PE investors would shift capital allocation towards firms that have potential to be affected by the advent of AI, which we classify using the AI exposure score from Felten et al (2021), defined in prior sections.

5.2 Sample selection and descriptive statistics

We test our research question, we rely on two different samples. First, to examine whether PE investors shifted their investment behavior, we construct an industry-year panel that aggregates the number of PE transactions across industries (at the SIC two-digit level) on an annual basis. As this sample does not require firms to be matched with other datasets (BurningGlass, Aberdeen, D&B), we aggregate 80,220 transactions from 2010-2021 for each industry year.

To construct the second sample, we focus on portcos under PE ownership before and after AlexNet and track their digital investment across this event. To construct this sample, we restrict our original portco sample (generated in section 3.1) to firms that received investment before 2012 (i.e., 2010 and 2011), to ensure that these firms are under PE ownership at the time of AlexNet introduction. Under these restrictions, we obtain 1,335 PE transactions that are matched to D&B database and BurningGlass data. We then isolate the 245 transactions that have valid sales/employee/job postings information in 2012. After nearest-neighbor matching, we construct the final sample of 198 treated transactions with 198 control firms.

In Figure 4, we plot the mean number of PE transactions for each industry-year. The blue bars (orange bars) in this figure represent the number of deals for high (low) AIIE industries. Consistent with our prediction, we observe a jump in PE transactions post 2012 for high AIIE industries. Specifically, in 2011 (a year before Alexnet) the mean number of transactions was approximately 7; in 2014, this number increases to about 9. Meanwhile, we observe muted effects for targets in low AIIE industries before and after AlexNet.

Table 7 reports the descriptive statistics for the BurningGlass sample which we restrict to existing portcos before and after AlexNet, described above. Panel A reports the type of PE transactions, and shows that there are 157 (117) growth equity (buyout) transactions in the sample, and 56 (217) non-IT (IT) firms. Panel B shows the firm characteristics; the firms are larger than the sample reported in Table 1, with a mean number of employees and sales of 868.52 and 204.88, respectively. Meanwhile, the number of digital job postings is slightly lower, with a mean value of 10.52 postings.

5.3 Research design

For both samples, we employ a differences-in-differences strategy. To first analyze whether the number of transactions increased post AlexNet, we again utilize the AI suitability measure used in section 4.4.2. As AlexNet is a breakthrough in the field of AI, we anticipate PE investors to increase investments into industries with high AI suitability. Thus, we consider high AIIE industries as the 'treated' industries, and the rest as control. To test this hypothesis, we implement the following poisson regression model:

$$Y_{ind,t} = \beta_1 High\ AIIE_{ind} \times Post\ (AlexNet)_t + \alpha_{ind} + \alpha_t + \varepsilon_{ind,t} \qquad (2)$$

Where $Y_{ind,t}$ denotes the number of PE transactions completed in a given industry and year; $High\ AIIE_{ind}$ is a dummy variable that equals one if the industry is defined as an industry with high AI suitability, and zero otherwise; $Post\ (AlexNet)_t$ equals one if the year is 2013 onwards, as AlexNet was introduced in September 2012, and zero otherwise. α_{ind} and α_t indicate industry and year fixed effects to control for time-invariant industry characteristics and time characteristics, respectively. Standard errors are clustered at the industry level.

To assess whether portcos under PE ownership change their investment behavior post AlexNet, we estimate the following model:

$$Y_{i,t} = \beta_1 High\ AIIE_{i,t} \times Post\ (AlexNet)_t + \gamma X' + \alpha_i + \alpha_t \qquad (3)$$

Where $Y_{i,t}$ is the proportion of machine learning and digital job postings (both scaled by total number of job postings). The reason for focusing on machine learning postings is that we expect AlexNet to have a more direct impact on machine learning within various skillsets related to new digital technologies.

5.4 AlexNet and digital targets

Table 8 reports the regressions described in equation (2). Columns (1) and (2) ((3) and (4)) report results without (with) industry fixed effects. Year fixed effects are included across all specifications. Including industry fixed effects increases the R-squared from 0.0893 to 0.8008 (columns (1) vs. (3)), indicating that most variation in our data can be explained by this choice. The coefficients in column (1) and (3) indicate that the number of target firms with high AI suitability increases by 19.7% (in column (3)) post AlexNet, andemoving industry fixed effects increases the magnitude to 26.9%. Columns (2) and (4) of the same table presents the dynamic effects of the AlexNet test, and validates that there are no statistically significant pre-trends during the pre-period, with economically small magnitude.

Overall, the evidence suggests that PE investors target firms more frequently that are more likely to be affected by AI, aftera major breakthrough in AI technologies. This resonates with the notion that PE investors' are able to identify opportunities in investing in digital technologies, which shapes how they allocate capital.

5.5 AlexNet and existing portfolio companies

Next, in Table 9, we examine whether PE portcos increase investment in AI-related technology in portfolio firms post AlexNet, by estimating equation (3). Columns (1) and (2) of Panel A, show that post AlexNet, PE portcos in high AIIE industries exhibit a significant increase in machine learning job postings by 3.6% (and 3.1% with firm fixed effects). Similarly, columns (3) and (4) demonstrate a significant increase in digital job postings post AlexNet as well. However, the economic magnitude is much smaller, as the coeffcients indicate around a 0.5% increase for both specifications.

Panel B shows the dynamic effects of the regressions in Panel A. We again do not observe significant pre-trends for years 2010 and 2011, reducing concerns that our results may be driven by the overall attractiveness of the high AI suitability industries.

5.6 PE entry and digital technology - before and after AlexNet

Recall that in Table 2 we demonstrate that PE entry into portcos is associated with greater IT investments. In the following analysis, we also test whether this association changes pre and post AlexNet. To conduct this analysis, we restrict the main sample used in Table 2 to high AI suitability portcos that are active pre and post AlexNet, and re-estimate equation (1).

In Table 10 Panel A (Panel B) we use machine learning (digital) job postings as the dependent variable to study the relationship between PE entry on digital investmentsOur analysis shows that this relationship was much weaker before AlexNet. Specifically, column (1) reports an statistically insignificant coefficient on $Treat\ x\ Post$ when we restrict our sample to years before AlexNet. On the other hand, column (2) reports a positive and meaningful coefficient on the DiD estimator, and this coefficient is also significantly different from the same coefficient in column (1). Similarly, Panel B reports the same regressions but using the proportion of digital job postings as the dependent variable. In this Panel, we also observe insignificant (significant) coefficients when we use years before (after) AlexNet in column (1) (column (2)). Overall, this result further supports the notion that PE investors change their investment behavior on their portcos when there is a meaningful advancement in technology.

5.7 Cross-sectional results - investor expertise

Similar to the results described in Table 5, we examine whether the effects are stronger for portcos that are governed by PE investors with more exposure to digital technology. Using the same portfolio firm-level sample used in Table 5, we test whether the observed effect of AlexNet on existing portfolio firms is stronger for firms with PE board members with IT firm board experience. Specifically, in Table 11, we use the cross-sectional variable $Portco\ Digital\ Board_d$, defined as a dummy variable (in Panel A) that equals one if there is at least one board member that has sat on an IT company, and zero otherwise, or the count (in Panel B) of the board members having IT board experience. We interact this variable with $Treat_i\ x\ Post_{i,t}$ and estimate equation (3).

Consistent with our expectations, we find evidence that portcos with board members with IT board experience exhibit greater increases in digital investment following AlexNet. Specifically, Panel A column (2), which measures the effects of AlexNet on digital job postings, finds a significant relationship with the variable $Treat\ x\ Post\ x\ Portco\ Digital\ Board$, indicating that portcos with high AI exposure and board members with IT board experience, exhibit a higher increase in digital job postings. Moveover, Panel B also finds significant coefficient for the $Treat\ x\ Post\ x\ Portco\ Digital\ Board$ variable, which indicates that the number of board members with IT experience, incrementally increases the positive relationship between AlexNet and machine learning and digital job postings, in high AI exposed firms. Collectively, these results suggest that exposure to digital technology is associated with a greater increase in digital technology investments, particularly for firms backed by PE investors with more digital technology experience.

6. Conclusion

In this study, we study the role PE investors play in the adoption of new digital technologies, focusing on how these investors allocate capital and influence digital investment in portfolio firms. Overall, we find that PE investors play an important role in digital technology adoption as we find that the entry of PE investors into portfolio companies is associated with greater investments in digital technology. Moreover, using the AlexNet setting, we find that PE investors respond to technological breakthroughs by (i) allocating capital towards high AI potential firms and increasing digital investment in existing portfolio firms with high AI potential.

To explain our findings, we further show that PE investor experience in IT could be a reason that the main results are stronger when the PE investor has prior exposure to digital technology. Last, we also find suggestive evidence that the adoption of new digital technologies in PE-backed firms are associated with favorable portfolio firm outcomes, such as firm growth and innovation.

We contribute to academic literature in the following ways. First, we complement research on IT governance by introducing PE investors as external agents that can shape a firm's IT strategies. Second, by linking digital transformation to *private* firm growth, we contribute to the literature on the economics of IT. Third, we complement the private equity literature that studies the impact of private equity transactions. We show that PE investors, who are sophisticated investors in the private markets, facilitate digital transformations in their portfolio firms to accelerate their growth. Finally, we show that the determinants of PE investing are shifting towards firms that exhibit greater potential to be transformed using digital technology.

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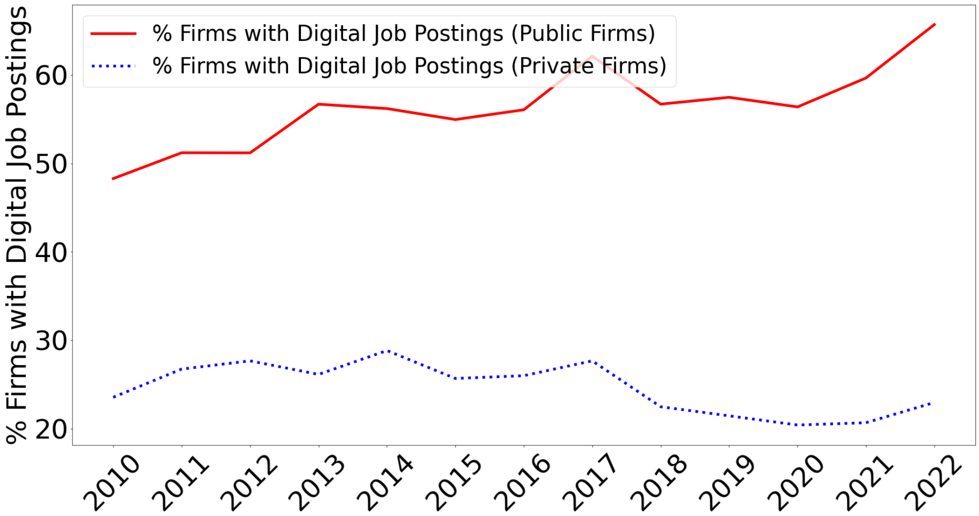
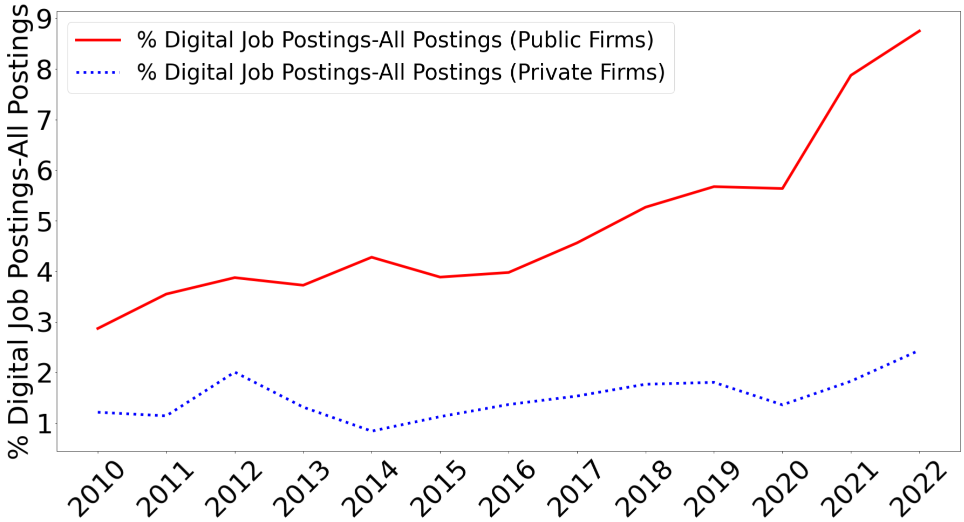
Appendix A: Variable Definitions

Variable Name	Variable Description
Digital Investment Variables:	
IT Budget	Total annual IT budgets across all facilities for each firm reported in *Aberdeen*.
Digital Job Postings	Total number of job postings with digital skills from *BurningGlass* in the calendar year. Digital skills are the machine learning, natural langauge processing, big data, data mining, data science, business intelligence and cloud skill clusters in *BurningGlass*.
ML Job Postings	Total number of job postings with skills in the machine learning cluster from *BurningGlass* in the calendar year.
Digital Board Member	Total number of PE-fund board members that also serve on boards of IT companies in the calendar year. (Measured using Pitchbook)
Deal Characteristics:	
IT Firm	Indicator coded as one if the portfolio firm is from an IT industry (based on the classification in Chen and Srinivasan, 2023).
Growth Equity Deal	Indicator coded a one if the private equity deal is classified as a growth equity injection.
High AI Potential	Indicator coded a one if the target firm is from an industry that is has an above median AI industry exposure (AIIE) as measured in Felten et al (2021).
Operating Variables:	
Log(Sales)	Logarithm of total annual sales, where sales is measured using *Dun and Bradstreet.*
Log(Employees)	Logarithm of total annual employees, where sales is measured using *Dun and Bradstreet.*
Sales-to-employees	Ratio of total annual sales to employees, where sales and employees are measured using *Dun and Bradstreet.*
Innovation Variables:	
Patents	Total number of patents filed in the calendar year, data taken from *USPTO.*
Adjusted Patents	Number of patents filed in the calendar year scaled by the total number of filed patents in the calendar year.

Tables and Figures



(a) % of Firms with Digital Job Postings



(b) % of Digital Job Postings-to-All Job Postings

Figure 1: Time-series Distribution of (a) % of Firms with Digital Job Postings and (b) % of Digital Job Postings-to-All Job Postings for Public and Private Companies

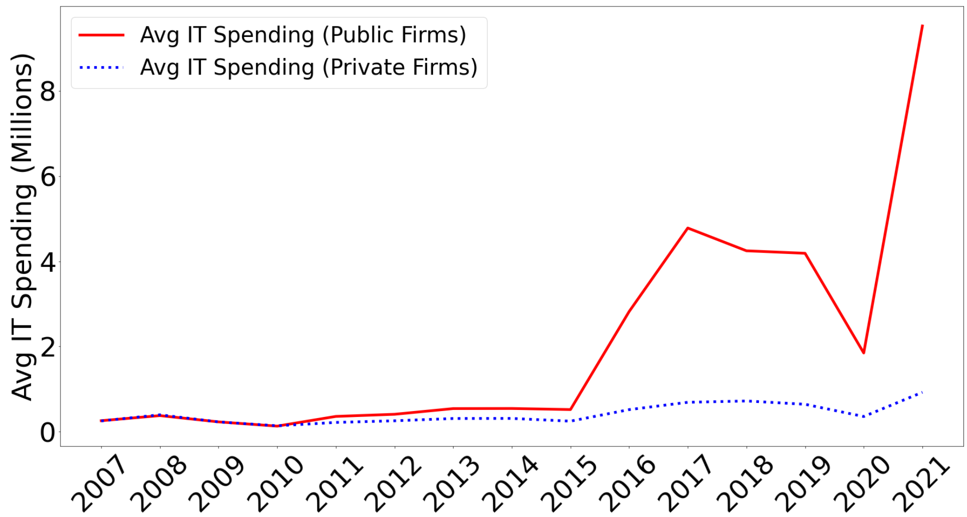
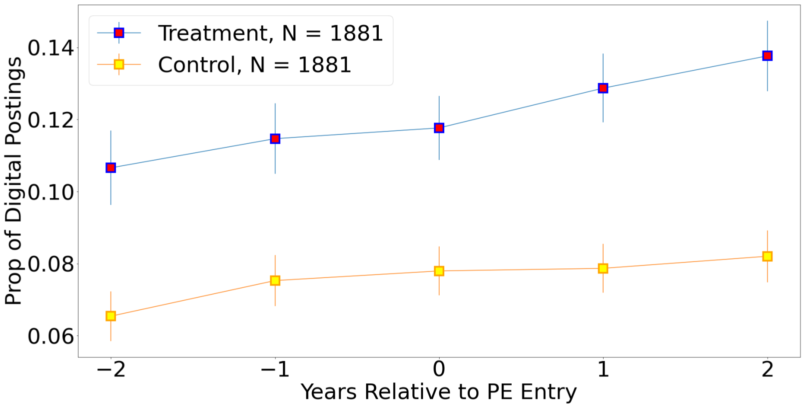
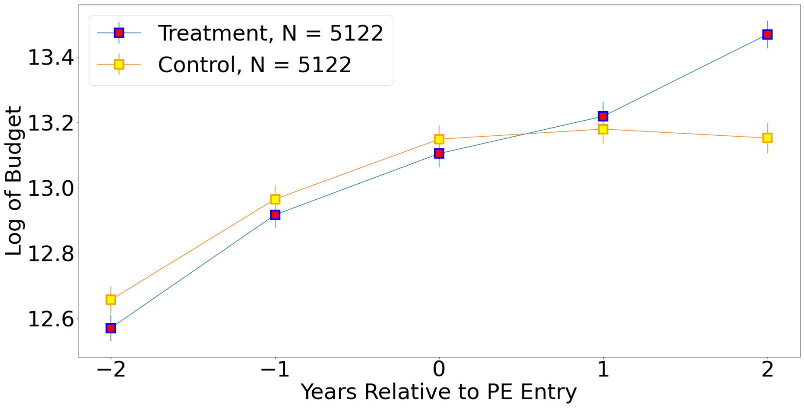


Figure 2: Time-series Distribution of Average IT Spending for Public and Private Companies



(a) Proportion of Digital Job Posting



(b) IT Budget

Figure 3: Digital Job Posting (Panel A) or Logarithm of IT budget (Panel B) around PE Investment Year for the Matched Sample of Portfolio Companies with 5-Year Consistent Time-Series. Error Bars Denote the 95% Confidence Interval.

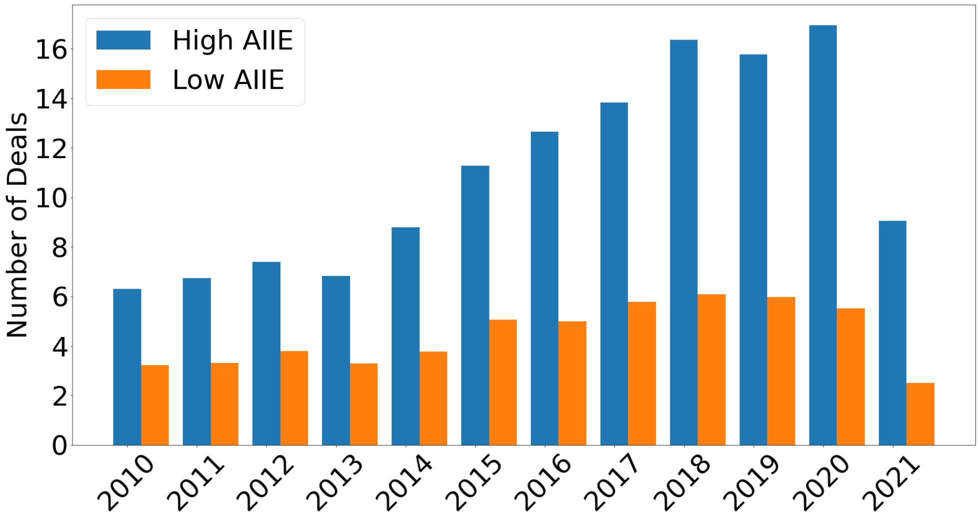


Figure 4: Time-series Distribution of Average Number of Deals in Industries with High or Low AI Industry Exposure (AIIE)

Table 1: Summary Statistics

This table reports the key summary statistics of our study. In Panel A, we present the number of PE deals in the *BurningGlass* and *Aberdeen* sample. We present the summary statistics across two samples — (1) the *BurningGlass* sample (in Panel B) which is used to measure digital job postings and (2) the *Aberdeen* sample which is used to measure IT-budgets (in Panel C). In Panel B, we present the statistics of seven variables, namely, the number of employees, sales in millions, sales growth, firm age, the number of digital job postings, the proportion of digital job postings and the total number of job postings. In Panel C, we present the statistics of five variables, namely, the number of employees, sales in millions, sales growth, firm age and IT budget in millions.

Panel A: Deal Breakdowns

	Deal Type		PortCo Type	
	Growth Equity	Buyout	Non-IT	IT
BurningGlass Sample	3935	2496	4548	1883
Aberdeen Sample	7129	5471	9466	3134

Panel B: BurningGlass Sample

	Mean	SD	Median	25%	75%	N
No. of Employees	145.09	137.85	91	22	301	38987
Total Sales (Millions)	23.77	22.53	14.81	2.7	56.3	38987
Sales Growth	0.21	0.61	0	0	0.13	38987
Firm Age	20.86	19.96	15	8	27	38987
No. of Digital Job Postings	27.71	388.76	0	0	5	38987
Prop. of Digital Job Postings	0.1	0.19	0	0	0.11	38987
Total Postings	360.41	2866.97	17	4	79	38987

Panel C: Aberdeen Sample

	Mean	SD	Median	25%	75%	N
No. of Employees	188.89	282.73	63	22	201	94399
Total Sales (Millions)	33.41	46.7	11.67	3.39	38.88	94399
Sales Growth	0.08	0.37	0	-0.01	0.07	94399
Firm Age	23.31	20.42	18	9	31	94399
IT Budget (Millions)	12.88	1.89	12.71	11.51	14.05	94399

Table 2: PE Entry and Digital Investment

This table reports the regression analysis of IT budgets and Digital job postings on the PE entry event. In columns (1) and (2), we examine the proportion of digital job postings relative to total job postings as the dependent variable and in columns (3) and (4) we examine the logarithm IT budgets as the dependent variable. The treatment firms are those that have received PE investment at some point in the sample, and the control firms are matched within the same 2-digit SIC industry, by size (log(sales)) and the level of IT budget (or the level of digital job postings for the *BurningGlass* sample) in the year before the PE entry. For each treatment and control pair, we keep observations within 2 years from the PE entry year (i.e. years -2, -1, 0, 1, 2 relative to the PE entry year). Control variables include the log of sales, employees, age and sales growth. Standard errors are clustered at the firm and year-level. ***, **, * denote significance at the 1%, 5% and 10% level.

Panel A: Main Analysis

	(1)	(2)	(3)	(4)
	Proportion of Digital Postings	Proportion of Digital Postings	Log(IT Budget)	Log(IT Budget)
Treat_i	0.046***		-0.052***	
	(0.005)		(0.016)	
$\text{Treat}_i \times \text{Post}_{i,t}$	0.015**	0.015***	0.205**	0.206***
	(0.006)	(0.003)	(0.073)	(0.060)
Firm FE	No	Yes	No	Yes
Matched Pair-Year FE	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes
Observations	38,987	38,987	94,399	94,399
R^2	0.6423	0.8955	0.9370	0.9731

Panel B: Main Analysis - Pre and Post

	(1)	(2)
	Proportion of Digital Postings	Log(IT Budget)
$\text{Treat}_i \times \text{Pre}_{i,t=-2}$	0.000	-0.059
	(0.003)	(0.049)
$\text{Treat}_i \times \text{Pre}_{i,t=-1}$	0.002	-0.026
	(0.004)	(0.036)
$\text{Treat}_i \times \text{Post}_{i,t=1}$	0.014***	0.143***
	(0.003)	(0.044)
$\text{Treat}_i \times \text{Post}_{i,t=2}$	0.018***	0.260***
	(0.003)	(0.058)
Firm FE	Yes	Yes
Matched Pair-Year FE	Yes	Yes
Controls	Yes	Yes
Observations	38,987	94,399
R^2	0.8956	0.9732

Table 3: Cross-Sectional Analysis: IT Budgets in High/Low IT-to-Sales Firms

This table reports the regression analysis of IT budgets, across firms with high/low IT-to-Sales before the PE entry event. In Panel A, we examine IT budgets across firms with below and above median IT-to-sales within the industry-year before PE investment. In Panel B, we examine the interaction of the PE investment with the above-median indicator of IT-to-Sales before the PE entry. The treatment firms are those that have received PE investment at some point in the sample, and the control firms are matched within the same 2-digit SIC industry, by size (log(sales)) and the level of IT budget in the year before the PE entry. For each treatment and control pair, we keep observations within 2 years from the PE entry year (i.e. years -2, -1, 0, 1, 2 relative to the PE entry year). Control variables include the log of sales, employees, age and sales growth. For all columns, we implement poisson regressions. Standard errors are clustered at the firm and year-level. ***, **, * denote significance at the 1%, 5% and 10% level.

Panel A: Main Analysis

	(1)	(2)
Sample	Low IT-to-Sales before PE Investment	High IT-to-Sales before PE Investment
Dependent Variable	IT Budget	IT Budget
$\text{Treat}_i \times \text{Post}_{i,t}$	0.229***	0.087
	(0.064)	(0.057)
Firm FE	Yes	Yes
Year FE	No	No
Matched Pair-Year FE	Yes	Yes
Controls	Yes	Yes
Observations	76,065	18,334
R^2	0.9705	0.9784

Panel B: Interaction Analysis

	IT Budget
$\text{Treat}_i \times \text{Post}_{i,t}$	0.228***
	(0.064)
$\text{Treat}_i \times \text{Post}_{i,t} \times$ Above Median IT-to-Sales Before PE Invest	-0.129**
	(0.049)
Firm FE	Yes
Year FE	No
Matched Pair-Year FE	Yes
Controls	Yes
Observations	94,399
R^2	0.9732

Table 4: Cross-Sectional Analysis: AI Potential, Non-IT Firms and Buyout Deals

This table reports the regression analysis of digital job postings and IT budgets on the PE entry event and the nature of the PE deal. In Panel A, we examine the proportion of digital postings relative to total job postings and the logarithm of IT budgets for portfolio companies that are either in high AI potential industries or low AI potential industries. In Panel B, we examine the proportion of digital postings relative to total job postings and the logarithm of IT budgets for portfolio companies that are either IT or non-IT. In Panel C, we examine the proportion of digital postings relative to total job postings and the logarithm of IT budgets for PE deals that are classified as either buyouts or growth deals. The treatment firms are those that have received PE investment at some point in the sample, and the control firms are matched within the same 2-digit SIC industry, by size (log(sales)) and the level of IT budget (or the level of digital job postings for the BurningGlass sample) in the year before the PE entry. For each treatment and control pair, we keep observations within 2 years from the PE entry year (i.e. years -2, -1, 0, 1, 2 relative to the PE entry year). Control variables include the log of sales, employees, age and sales growth. For Column (1), we implement poisson regressions. Standard errors are clustered at the firm and year-level. ***, **, * denote significance at the 1%, 5% and 10% level.

Panel A: AI Potential

	(1)	(2)
Dependent Variable	Proportion of Digital Posting	Log(IT Budget)
$\text{Treat}_i \times \text{Post}_{i,t}$	0.004	0.148**
	(0.005)	(0.054)
$\text{Treat}_i \times \text{Post}_{i,t} \times \text{High AIIE}_d$	0.017**	0.074**
	(0.006)	(0.029)
Firm FE	Yes	Yes
Year FE	No	No
Matched Pair-Year FE	Yes	Yes
Controls	Yes	Yes
Observations	31,159	74,831
R^2	0.8949	0.9724

Panel B: Non-IT and IT Firms

	(1)	(2)
Dependent Variable	Proportion of Digital Posting	Log(IT Budget)
$\text{Treat}_i \times \text{Post}_{i,t}$	0.010**	0.192***
	(0.003)	(0.055)
$\text{Treat}_i \times \text{Post}_{i,t} \times \text{IT}_d$	0.017*	0.062*
	(0.008)	(0.034)
Firm FE	Yes	Yes
Year FE	No	No
Matched Pair-Year FE	Yes	Yes
Controls	Yes	Yes
Observations	38,987	94,399
R^2	0.8956	0.9731

Panel C: Growth Equity and Buyout Deals

	(1)	(2)
Dependent Variable	Proportion of Digital Posting	Log(IT Budget)
$\text{Treat}_i \times \text{Post}_{i,t}$	0.014***	0.144**
	(0.004)	(0.046)
$\text{Treat}_i \times \text{Post}_{i,t} \times \text{Growth}_d$	0.002	0.112***
	(0.005)	(0.031)
Firm FE	Yes	Yes
Year FE	No	No
Matched Pair-Year FE	Yes	Yes
Controls	Yes	Yes
Observations	38,987	94,399
R^2	0.8955	0.9732

Table 5: PE Investment, PE Expertise and Digital Transformation

This table reports the regression analysis of digital job postings and logarithm of IT budgets on the PE entry event and the digital technology expertise at the PE investor level. In Panel A, we perform the cross-sectional analysis for PE deals where the portfolio companies that have a PE fund board member with digital expertise (i.e. sits on the board of an IT firm) with data from pitchbook. In Panel B, we perform the same analysis for PE deals where the cross-sectional variable is the number of PE board member with digital expertise. The treatment firms are those that have received PE investment at some point in the sample, and the control firms are matched within the same 2-digit SIC industry, by size (log(sales)) and the level of IT budget (or the level of digital job postings for the BurningGlass sample) in the year before the PE entry. For each treatment and control pair, we keep observations within 2 years from the PE entry year (i.e. years -2, -1, 0, 1, 2 relative to the PE entry year). Control variables include the log of sales, employees, age and sales growth. For Column (1), we implement poisson regressions. Standard errors are clustered at the firm and year-level. ***, **, * denote significance at the 1%, 5% and 10% level.

Panel A: Digital Expertise Measured by the Presence of Digital PE Board Members

	(1)	(2)
Dependent Variable	Proportion of Digital Posting	Log(IT Budget)
$\text{Treat}_i \times \text{Post}_{i,t}$	0.007**	0.164***
	(0.002)	(0.046)
$\text{Treat}_i \times \text{Post}_{i,t} \times \text{PortCo Digital Board}_d$	0.021***	0.143**
	(0.005)	(0.058)
Firm FE	Yes	Yes
Matched Pair-Year FE	Yes	Yes
Controls	Yes	Yes
Observations	38,987	94,431
R^2	0.8957	0.9732

Panel B: Digital Expertise Measured by the Number of PE Fund Digital PE Board Members

	(1)	(2)
Dependent Variable	Proportion of Digital Posting	Log(IT Budget)
$\text{Treat}_i \times \text{Post}_{i,t}$	0.010***	0.177***
	(0.003)	(0.050)
$\text{Treat}_i \times \text{Post}_{i,t} \times \text{No. PortCo Digital Board}_d$	0.002**	0.018**
	(0.001)	(0.007)
Firm FE	Yes	Yes
Matched Pair-Year FE	Yes	Yes
Controls	Yes	Yes
Observations	38,987	94,431
R^2	0.8956	0.9732

Table 6: Post PE Entry Changes in Digital Investment and Firm Performance

This table reports the regression of the sales growth and employee growth on PE portfolio companies and invest in digital technologies around the PE entry event. To measure changes in firm performance, we measure the difference in $s+2$ and $s-1$ levels of firm performance around the PE entry year s, relative to the difference in firm performance over the same horizon in matched control firms. To measure changes in digital investment, we measure the difference in $s+2$ and $s-1$ levels of either the proportion of digital postings relative to total job postings or the logartihm of IT budgets around the PE entry year s relative to matched control firm changes over the same horizon. Panel A performs the analysis with log of sales and employees as dependent variables, while Panel B performs the analysis for changes in patenting activity (raw counts or relative to the total number of patents filed in the year). The job postings in Panel B are also defined using machine learning job postings instead of digital job postings. The treatment firms are those that have received PE investment in year s, and the control firms are matched within the same 2-digit SIC industry, by size (log(sales)) and the level of IT budget (or the level of digital job postings for the BurningGlass sample) in the year before the PE entry year s. Control variables are also defined in changes and include sales-to-employees for Panel A. We further include log of sales and log of employees as controls for Panel B. Standard errors are clustered at the firm level. ***, **, * denote significance at the 1%, 5% and 10% level.

Panel A: Sales and Employee Growth

Investment Variable	Digital Job Postings		Log(IT Budgets)	
Dependent Variable	Δ Log of Sales$_{s+2,s-1}$	Δ Log of Employees$_{s+2,s-1}$	Δ Log of Sales$_{s+2,s-1}$	Δ Log of Employees$_{s+2,s-1}$
	(1)	(2)	(3)	(4)
Δ Investment$_{s+2,s-1}$	0.001	0.001*	0.245***	0.183***
	(0.002)	(0.001)	(0.011)	(0.009)
Treatment Cohort FE	Yes	Yes	Yes	Yes
Observations	1,885	1,885	5,220	5,220
R^2	0.0711	0.0707	0.2939	0.2413

Panel B: Innovation Performance

Investment Variable	ML Job Postings		Log(IT Budgets)	
Dependent Variable	Δ Patent$_{s+2,s-1}$	Δ Adjusted Patent$_{s+2,s-1}$	Δ Patent$_{s+2,s-1}$	Δ Adjusted Patent$_{s+2,s-1}$
	(1)	(2)	(3)	(4)
Δ Investment$_{s+2,s-1}$	0.625**	0.017**	0.004	0.007
	(0.298)	(0.009)	(0.003)	(0.004)
Treatment Cohort FE	Yes	Yes	Yes	Yes
Observations	1,885	1,885	5,220	5,220
R^2	0.0120	0.0103	0.0052	0.0046

Table 7: AlexNet Sample Summary Statistics

This table reports the key summary statistics of the AlexNet analysis. In Panel A, we present the number of PE deals in the *BurningGlass* sample. Next, we present the summary statistics for the *BurningGlass* sample in Panel B. In Panel B, we present the statistics of five variables, namely, the number of employees, sales in millions, sales growth, firm age and IT budget in millions. In Panel C, we present the statistics of seven variables, namely, the number of employees, sales in millions, sales growth, firm age, the number of digital job postings, the proportion of digital job postings, the number of machine learning job postings, the proportion of machine learning job postings and the total number of job postings.

Panel A: Deal Breakdowns

	Deal Type		PortCo Type	
	Growth Equity	Buyout	Non-IT	IT
BurningGlass Sample	156	117	217	56

Panel B: BurningGlass Sample

	Mean	SD	Median	25%	75%	N
No. of Employees	868.52	1872.9	181	66	564	1993
Total Sales (Millions)	204.88	516.22	30.15	9.5	116.14	1993
Sales Growth	0.4	1.88	0	-0.03	0.16	1993
Firm Age	16.2	18.04	11	5	19	1993
No. of Digital Job Postings	10.52	42.55	0	0	3	1993
Prop. of Digital Job Postings	0.06	0.12	0	0	0.06	1993
No. of ML Job Postings	0.74	4.09	0	0	0	1993
Prop. of ML Job Postings	0	0.02	0	0	0	1993
Total Postings	272.64	1175.95	17	4	97	1993

Table 8: AlexNet and PE Targets

This table examines the relationship between the introduction of a breakthrough AI technology, AlexNet, and the number of PE deals in high AI potential industries. Across all columns, we regress the number of PE deals in the industry on an interaction of an indicator for whether the portfolio firm is in an industry that exhibits high AI potential (Felten et al, 2021) and an indicator for the years after AlexNet in 2012 for the sample of PE deals from 2010-2021. All regression models are implemented on an industry-year panel, with the dependent variable defined in counts and applied on a poisson distribution. Standard errors clustered at the industry and year-level are reported. ***, **, * denote significance at the 1%, 5% and 10% level.

	(1)	(2)	(3)	(4)
	Number of PE Deals	Number of PE Deals	Number of PE Deals	Number of PE Deals
High AIIE_j	0.680***	0.667***		
	(0.243)	(0.216)		
High $\text{AIIE}_j \times \text{Post(AlexNet)}_{y>2012}$	0.269***	0.282***	0.197**	0.191***
	(0.081)	(0.100)	(0.094)	(0.059)
High $\text{AIIE}_j \times \text{Post(AlexNet)}_{y=2011}$		0.041		0.077
		(0.053)		(0.072)
High $\text{AIIE}_j \times \text{Post(AlexNet)}_{y=2010}$		-0.001		-0.111
		(0.064)		(0.068)
Industry FE	No	No	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Observations	6,223	6,223	6,223	6,223
R^2	0.0893	0.0893	0.8008	0.8008

Table 9: AlexNet and Digital Investment in PE PortCos

This table examines the relationship between the introduction of a breakthrough AI technology, AlexNet, and the extent of digital investment in PE PortCos from high AI potential industries. In columns (1) and (2) of Panel A, we regress the proportion of machine learning job postings digital job postings on an interaction of an indicator for whether the portfolio firm is in an industry that exhibits high AI potential (Felten et al, 2021) and an indicator for the years after AlexNet in 2012 for the sample of PE PortCos from that were invested by PE before 2012. While in columns (3) and (4), we regress the proportion of digital job postings on the same set of independent variables. All regression models are implemented on an portco firm-year panel. Regressions also includes controls for sales growth, logarithm of sales and logarithm of employees. Standard errors clustered at the firm and year-level are reported. ***, **, * denote significance at the 1%, 5% and 10% level.

Panel A: Main Analysis

	(1)	(2)	(3)	(4)
	Proportion of Machine Learning Postings	Proportion of Machine Learning Postings	Proportion of Digital Postings	Proportion of Digital Postings
AIIE_i	0.010		-0.001	
	(0.008)		(0.001)	
$\text{AIIE}_i \times \text{Post}_{i,t>2012}$	0.036***	0.031***	0.005***	0.005***
	(0.009)	(0.009)	(0.001)	(0.002)
Firm FE	No	Yes	No	Yes
Year FE	Yes	Yes	Yes	Yes
Observations	1,993	1,993	1,993	1,993
R^2	0.0505	0.5554	0.0318	0.3783

Panel B: Pre- and Post-Trend Analysis

	(1)	(2)
	Proportion of Machine Learning Postings	Proportion of Digital Postings
$\text{AIIE}_i \times \text{Post}_{i,t>2012}$	0.032***	0.005***
	(0.008)	(0.001)
$\text{AIIE}_i \times \text{Post}_{i,t=2011}$	0.003	0.000
	(0.006)	(0.001)
$\text{AIIE}_i \times \text{Post}_{i,t=2010}$	0.004	0.000
	(0.005)	(0.001)
Firm FE	Yes	Yes
Year FE	Yes	Yes
Observations	1,993	1,993
R^2	0.5554	0.3783

Table 10: AlexNet, PE Entry and Digital Investment

This table examines the relationship between the introduction of a breakthrough AI technology, AlexNet, and the extent of digital investment after PE Entry. In Panel A, we examine whether PE entry increases the proportion of digital job postings for the years before and after AlexNet in 2012, for the sample of portcos in high AI exposure industries. In Panel B, we examine whether PE entry increases the proportion of machine learning postings for the years before and after AlexNet in 2012, for the sample of portcos in high AI exposure industries. All regression models are implemented on an portco firm-year panel. Regressions also includes controls for sales growth, logarithm of sales and logarithm of employees. Standard errors clustered at the firm and year-level are reported. ***, **, * denote significance at the 1%, 5% and 10% level.

Panel A: ML Job Postings		
	(1)	(2)
Sub-Sample	Before AlexNet	After AlexNet
Dep. Variable	Machine Learning Job Postings	Machine Learning Job Postings
$\text{Treat}_i \times \text{Post}_{i,t}$	-0.001	0.002**
	(0.001)	(0.001)
Firm FE	Yes	Yes
Matched Pair-Year FE	Yes	Yes
Controls	Yes	Yes
Observations	1,008	21,791
R^2	0.9678	0.8561
Δ $\text{Treat}_i \times \text{Post}_{i,t}$ βs	0.003***	
	(0.001)	
Firm FE	Yes	
Matched Pair-Year FE	Yes	
Controls	Yes	
Observations	22,799	
R^2	0.8567	

Panel B: Digital Job Postings		
	(1)	(2)
Sub-Sample	Before AlexNet	After AlexNet
Dep. Variable	Digital Job Postings	Digital Job Postings
$\text{Treat}_i \times \text{Post}_{i,t}$	-0.029	0.022***
	(0.022)	(0.003)
Firm FE	Yes	Yes
Matched Pair-Year FE	Yes	Yes
Controls	Yes	Yes
Observations	1,008	21,791
R^2	0.9697	0.8979
Δ $\text{Treat}_i \times \text{Post}_{i,t}$ βs	0.051**	
	(0.017)	
Firm FE	Yes	
Matched Pair-Year FE	Yes	
Controls	Yes	
Observations	22,799	
R^2	0.9003	

Table 11: AlexNet, PE Features and Digital Investment in PE PortCos

This table reports the cross-sectional analysis of machine learning and digital job postings of PE PortCos around the AlexNet event. In Panel A, we perform the cross-sectional analysis for PE deals where the portfolio companies have a PE fund board member with digital expertise (i.e. sits on the board of an IT firm) with data from pitchbook. In Panel B, we perform the same analysis for the cross-sectional variable defined as the number of PE board members. In Panel C, we perform the cross-sectional analysis for PE deals that are structured as growth equity deals or buyout deals. The treatment firms are those that have received PE investment and are in classified as highly exposed AI, and the control firms are the firms that have also received PE investment but are classified as less exposed to AI. For each treatment and control pair, we keep observations within 2 years from the PE entry year (i.e. years -2, -1, 0, 1, 2 relative to the PE entry year). Control variables include the log of sales, employees, age and sales growth. Standard errors are clustered at the firm and year-level. ***, **, * denote significance at the 1%, 5% and 10% level.

Panel A: Digital Expertise Measured by the Presence of PE Fund Digital Board Members

	(1)	(2)
	Proportion of Machine Learning Postings	Proportion of Digital Postings
$\text{AIIE}_i \times \text{Post}_{i,t>2012}$	0.024**	0.003**
	(0.009)	(0.001)
$\text{AIIE}_i \times \text{Post}_{i,t>2012} \times \text{Digital Board}_{p,t}$	0.027	0.006**
	(0.015)	(0.003)
Firm FE	Yes	Yes
Year FE	Yes	Yes
Observations	1,993	1,993
R^2	0.5563	0.3810

Panel B: Digital Expertise Measured by the Number of PE Fund Digital Board Members

	(1)	(2)
	Proportion of Machine Learning Postings	Proportion of Digital Postings
$\text{AIIE}_i \times \text{Post}_{i,t>2012}$	0.023**	0.004***
	(0.008)	(0.001)
$\text{AIIE}_i \times \text{Post}_{i,t>2012} \times \text{No. Digital Board}_{p,t}$	0.005*	0.001**
	(0.003)	(0.000)
Firm FE	Yes	Yes
Year FE	Yes	Yes
Observations	1,993	1,993
R^2	0.5578	0.3823

Panel C: Growth Equity and Buyout Deals

	(1)	(2)
	Proportion of Machine Learning Postings	Proportion of Digital Postings
$\text{AIIE}_i \times \text{Post}_{i,t>2012}$	0.071***	0.006***
	(0.018)	(0.002)
$\text{AIIE}_i \times \text{Post}_{i,t>2012} \times \text{Growth}_i$	-0.060***	-0.001
	(0.017)	(0.002)
Firm FE	Yes	Yes
Year FE	Yes	Yes
Observations	1,993	1,993
R^2	0.5608	0.3785

Internet Appendix: Tables

Table IA.1: Covariate Balance

This table presents the difference in treatment and control groups. We examine, log of sales and log of employees. Columns 1-4 presents the sample statistic of the treated firms and columns 5-8 presents the same for the control firms. Differences in the mean is reported in column 9 with the independent 2-sample t-test statistic. Panel A reports the covariate balance of the Aberdeen sample, and Panel B reports the covariate balance of the BurningGlass sample. ***, **, * denote significance at the 1%, 5% and 10% level.

Panel A: Aberdeen Sample									
	Treated				Control				Differences
	Mean	SD	Median	N	Mean	SD	Median	N	Mean
Log Employees	4.14	1.49	4.06	12585	4.14	1.54	4.03	12585	0
Log Sales	16.08	1.96	16.21	12585	16.06	1.86	16.12	12585	0.02
Panel B: BurningGlass Sample									
	Treated				Control				Differences
	Mean	SD	Median	N	Mean	SD	Median	N	Mean
Log Employees	3.96	1.57	4.16	6449	3.98	1.62	4.26	6449	-0.02
Log Sales	15.56	2.57	16.18	6449	15.59	2.61	16.24	6449	-0.03

Table IA.2: PE Entry and the Types of IT Investments

This table reports the regression analysis of the various types of IT budgets on the PE entry event. For the dependent variable, we examine hardware IT budgets, software IT budget, and communication IT budgets, data storage budget, IT services budget and other IT budgets. The treatment firms are those that have received PE investment at some point in the sample, and the control firms are matched within the same 2-digit SIC industry, by size (log(sales)) and the level of IT budget in the year before the PE entry. For each treatment and control pair, we keep observations within 2 years from the PE entry year (i.e. years -2, -1, 0, 1, 2 relative to the PE entry year). For Columns (1)-(3), we use observations from 2010-2021, while for Columns (4)-(6) we use observations from 2010-2019 due to data availablity. Control variables include the log of sales, employees, age and sales growth. Standard errors are clustered at the firm and year-level. For all columns, we implement poisson regressions. ***, **, * denote significance at the 1%, 5% and 10% level.

	(1)	(2)	(3)	(4)	(5)	(6)
	Hardware Budget	Software Budget	Comm. Budget	Data Storage Budget	IT Services Budget	Other IT Budget
$\text{Treat}_i \times \text{Post}_{i,t}$	0.208***	0.206***	0.197**	0.220**	0.179***	0.209**
	(0.061)	(0.061)	(0.074)	(0.087)	(0.053)	(0.079)
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Matched Pair-Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Observations	94,399	94,399	94,399	68,795	68,795	68,795
R^2	0.9729	0.9731	0.9543	0.9636	0.9784	0.9719

Table IA.3: PE Entry and Digital Hiring

This table reports the regression analysis of digital job postings on the PE entry event. Across the columns, we examine the proportion of machine learning, data science, natural language processing, big data, data mining, business intelligence, and cloud job postings, relative to total job postings. The treatment firms are those that have received PE investment at some point in the sample, and the control firms are matched within the same 2-digit SIC industry, by size (log(sales)) and the level of digital job postings in the year before the PE entry. For each treatment and control pair, we keep observations within 2 years from the PE entry year (i.e. years -2, -1, 0, 1, 2 relative to the PE entry year). Control variables include the log of sales, employees, age and sales growth. Standard errors are clustered at the firm and year-level. ***, **, * denote significance at the 1%, 5% and 10% level.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	ML	Data Science	NLP	Big Data	Data Mining	BI	Cloud
$\text{Treat}_i \times \text{Post}_{i,t}$	0.001**	0.002**	-0.000	-0.000	-0.000	0.003**	0.012***
	(0.000)	(0.001)	(0.000)	(0.001)	(0.000)	(0.001)	(0.002)
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Matched Pair-Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	38,987	38,987	38,987	38,987	38,987	38,987	38,987
R^2	0.8554	0.8587	0.8345	0.8734	0.7711	0.8193	0.9014

Table IA.4: Post PE Entry Changes in Digital Investment and Firm Performance (Indicator Version)

This table reports the regression of the sales growth and employee growth on PE portfolio companies and invest in digital technologies around the PE entry event. To measure changes in firm performance, we measure the difference in $s+2$ and $s-1$ levels of firm performance around the PE entry year s, relative to the difference in firm performance over the same horizon in matched control firms. To measure changes in digital investment, we use an indicator that is coded as 1 if the firm exhibits a positive difference in $s+2$ and $s-1$ levels of either the proportion of digital postings relative to total job postings or the logartihm of IT budgets around the PE entry year s relative to matched control firm changes over the same horizon, and 0 otherwise. Panel A performs the analysis with log of sales and employees as dependent variables, while Panel B performs the analysis for changes in patenting activity (raw counts or relative to the total number of patents filed in the year). The job postings in Panel B are also defined using machine learning job postings instead of digital job postings. The treatment firms are those that have received PE investment in year s, and the control firms are matched within the same 2-digit SIC industry, by size (log(sales)) and the level of IT budget (or the level of digital job postings for the BurningGlass sample) in the year before the PE entry year s. Control variables are also defined in changes and include sales-to-employees for Panel A. We further include log of sales and log of employees as controls for Panel B. Standard errors are clustered at the firm level. ***, **, * denote significance at the 1%, 5% and 10% level.

Panel A: Sales Growth and Employee Growth

Investment Variable	Digital Job Postings		Log(IT Budgets)	
Dependent Variable	Δ Log of Sales$_{s+2,s-1}$	Δ Log of Employees$_{s+2,s-1}$	Δ Log of Sales$_{s+2,s-1}$	Δ Log of Employees$_{s+2,s-1}$
	(1)	(2)	(3)	(4)
Increase Investment$_{s+2,s-1}$	0.131	0.206***	0.608***	0.460***
	(0.124)	(0.046)	(0.026)	(0.022)
Treatment Cohort FE	Yes	Yes	Yes	Yes
Observations	1,885	1,885	5,220	5,220
R^2	0.0715	0.0783	0.2261	0.1865

Panel B: Innovation Performance

Investment Variable	ML Job Postings		Log(IT Budgets)	
Dependent Variable	Δ Patent$_{s+2,s-1}$	Δ Adjusted Patent$_{s+2,s-1}$	Δ Patent$_{s+2,s-1}$	Δ Adjusted Patent$_{s+2,s-1}$
Increase Investment$_{s+2,s-1}$	0.145*	0.004	-0.001	0.001
	(0.085)	(0.002)	(0.008)	(0.011)
Treatment Cohort FE	Yes	Yes	Yes	Yes
Observations	1,885	1,885	5,220	5,220
R^2	0.0135	0.0109	0.0047	0.0039