Private Equity and the Adoption of New Technologies: Evidence from Digital Technology Investment

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Abstract

We investigate the role of private equity (PE) investors as an intermediary in the adoption of new technologies in private firms. Using a unique dataset that contains information on technology investments, we first document a significant increase in investments in new technologies for portfolio firms post PE investment. The effect is pronounced for firms likely to be affected by technological advancements and for those with investors with expertise in technology. We also show that the adoption of new technologies is related to better firm growth. We then investigate whether PE investors respond to technological shocks by reallocating capital. Using a plausibly exogenous development in artificial intelligence (AI), we find that PE investors (i) shift their target investments to firms that are likely to be affected by AI and (ii) increase their existing AI-affected portfolio firms' digital technology investments. Overall, we introduce PE investors as an important intermediary for enhancing technology adoption in private firms.

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

JEL Codes: G24; G32; O33

1. Introduction

Technological change is critical for economic growth (e.g., Romer, 1990; Aghion and Howitt, 1992; Kogan et al., 2017). However, the benefits of advanced technology can only emerge if firms understand how to adopt it and do so (Hall and Khan, 2003). For example, while public superstar firms make large investments into digital capital (Tambe et al., 2020), advanced technology adoption is rare among small private firms (Zolas et al., 2020). Tambe et al. (2020) further argue that only a few firms have enough knowledge to effectively implement new technology, which highlights the importance of expertise in this realm.[1]

We study whether private equity (PE) investors act as intermediaries in private firms' adoption of new technologies. Specifically, we investigate two questions: (i) Do PE investors make investments into new technologies once they invest in the portfolio firm? (ii) Do PE investors respond to technological advancements by reallocating their capital? PE investors typically seek to improve portfolio firms' operational efficiency (e.g., Bernstein and Sheen, 2016; Davis et al., 2014; Gompers et al., 2016) and adopting new technology can help with this (e.g., Bresnahan, Brynjolfsson, and Hitt, 2002; Cockburn et al., 2018). However, as PE investors are thought to invest in traditional industries with stable cash flows (e.g., Opler and Titman, 1993; Stafford, 2022), they may not invest in new technology or alter their investments on account of technological developments. Furthermore, investing in new technologies is costly (e.g., Matthews et al., 2009)—perhaps even more so today, as the latest wave of digital technologies requires investments into intangible and organizational capital (Tambe et al., 2020).

[1] See Figures 1 and 2 for an illustration of IT-related demand (in terms of digital technology job postings and IT expenses) which illustrate a similar point.

To examine our first question, we focus on whether firm investments into digital technology, especially IT infrastructure and related personnel, increase post PE investment. To do so, we first construct a unique dataset that combines information on digital investments and PE transactions. To capture digital investments, we focus on the job postings provided by BurningGlass Technologies and Aberdeen that measure labor demand and IT-related expenses, respectively, for specific types of digital technologies. Second, we match this data to a list of PE transactions from 2010–2021 (collected from Capital IQ, Preqin, and Pitchbook) and establishment-level sales and employees data from Dun and Bradstreet (D&B). Our unit of observations is at the portfolio firm-year level, with 6,532 (6,431) PE transactions in the BurningGlass (Aberdeen) sample.

Our main research design employs a stacked differences-in-differences strategy, where the treated firms are the ones that experience a PE transaction.[2] The control firms are obtained from D&B and are in the same industry, with similar sales, employment, and digital investment in the year of the treated firm's PE transaction. The main dependent variables are the proportion of the number of digital job postings (following the digital-related skills clusters provided by BurningGlass and used by Goldfarb et al., 2023) scaled by the total number of job postings and the natural log of the dollar amount of IT budget (from the Aberdeen dataset following He et al., (2022) and Charoenwong et al. (2024)).

In our main analysis, we find a statistically significant increase in IT-related investments. Economically, the coefficients indicate a 1.5 percentage point increase in the proportion of digital job postings and a 20.5% increase in portfolio firm IT budget. This translates to 15% of the mean

[2] To reduce biases from treatment effects heterogeneity (Baker et al., 2022), we employ a stacked regression design that averages the difference-in-differences estimator over matched treatment and control groups.

proportion of digital job postings and $2.64 million in IT budgets, respectively. The main results are consistent with our hypothesis that PE investors expand portfolio firms' investments in digital technologies. We validate our main results by demonstrating the absence of pre-trends through dynamic regressions.

Next, we explore whether the PE deal characteristics are associated with heterogeneous effects. First, we exploit the variation at the portfolio firm/deal level. Specifically, we find that the effects strengthen for industries with high artificial intelligence (AI) suitability, a proxy developed by Felten et al. (2021) that measures the extent to which AI may affect an industry. For industries with high AI suitability, portfolio firms should increase investments into digital infrastructure to prepare for technological advances, and our analysis suggests that PE investors make more digital investments in these industries.

Furthermore, we find that, while the magnitude of increase is larger for most digital outcomes for IT portfolio firms, the results still hold for non-IT portfolio firms. This reduces the concern that only portfolio firms in the IT industry may drive our results and is consistent with the argument that PE investors invest in technology even at non-IT firms (also in line with Chen and Srinivasan, 2024, Chen, 2024). We also find that the effects on digital investment strengthen slightly for growth equity investments but also hold for buyouts. This finding is consistent with the notion that the digital investments that our main results hold across different deal structures and are perhaps more prominent in growth equity deals, which focus more on expanding the portfolio firm's business.

We then present tests exploiting variation at the PE investor level, specifically the PE investor's new technology expertise. Our conjecture is that PE investors with more expertise would be more likely to invest in digital technologies because they will know which cutting-edge

technologies will enhance their investments. We find stronger results for portfolio firms backed by PE investors with technology exposure. Specifically, we show that the results strengthen for portfolio firms invested by PE investors that have served on boards of IT firms and are even stronger if a board has more members with IT expertise. The results are consistent with the findings of Bernstein and Sheen (2016) that investors with industry expertise mainly drive operational improvements in PE portfolio firms.

We also examine the consequences of digital transformation in two ways. First, research suggests that the adoption and integration of digital technologies is associated with enhanced productivity and the development of new products and services (Babina et al., 2024). We find that portfolio firms with a greater increase in digital investments post PE entry are associated with faster sales and employee growth if PE entry is linked to more digital job postings or higher IT budgets.

Second, we test whether digital investments are related to innovation. As extant research argues that advanced digital technologies such as AI and machine learning could affect innovation by improving the R&D process (Cockburn et al., 2018), we focus on increases in machine learning hiring. We find that increases in machine learning job postings post PE investment are associated with a greater 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 do IT budgets, as IT budgets reflect digital investments that serve many purposes.

To examine our second research question, whether PE investors reallocate capital in response to advances in technology, we exploit the introduction of AlexNet, an AI breakthrough. AlexNet, introduced in September 2012, is a convolutional neural network that significantly

reduced error rates of visual recognition (LeCun et al., 2015; Krizhevsky et al., 2017). Exploiting this setting, we investigate whether the introduction of AlexNet influenced PE investors to invest in firms in industries with high AI suitability (discussed above, from Felten et al., 2021). To do so, we compile PE transactions in 2010–2021 from three data sources—Preqin, Pitchbook, and Capital IQ—and aggregate the number of transactions for each industry-year (SIC four-digit code). We then estimate differences-in-differences regressions where we regress the number of PE transactions on the interaction between the high AI suitability indicator and post-AlexNet indicator (2012 and onward).

Consistent with the argument that PE investors began to shift their investments after a technological breakthrough, we find that PE investors are more likely to target firms with high AI suitability following AlexNet's introduction. Our Poisson regression results suggest that the number of PE deals in high AI exposure industries increases by 19.1% post AlexNet's release. Our results are robust to including industry and year fixed effects, and we do not observe any pre-trends. Overall, the results support the argument that PE investors respond to advances in technology.

Next, we investigate whether existing PE portfolio firms invest in new technologies after a breakthrough in technology. To test this conjecture, we construct a dataset, similar to the one used in first part of our study, that links the PE transactions with job postings from BurningGlass but instead restricts the analysis to PE transactions after 2010 (as they need to be active at AlexNet). Using this sample, we test whether the portfolio firms with high AI exposure increase their AI-related (i.e., digital technology and machine learning) job postings post AlexNet's introduction.[3]

[3] We do not use IT budgets as the dependent variable in this setting because the shock is specific to artificial intelligence, which the IT budget has a limited ability to capture.

We find a 3.1 percentage (0.5%) point increase in the digital (machine learning) job postings (scaled by the total number of job postings) for high AI-exposure portfolio firms post AlexNet. We also find an absence of pre-trends with our results.

To tie our first set of analyses to the AlexNet setting, we further examine whether the association between PE entry and digital technology investment weakens (strengthens) before (after) AlexNet for digital and machine learning job postings. We test this association by examining whether these job postings increase post PE investment compared to control firms in the same period, before and after AlexNet. We find little (significant) relation for both types of job postings before (after) AlexNet, and the coefficients differ significantly.

We further test whether our findings on digital investments after AlexNet strengthen when the portfolio firm has a board member with technology expertise. As in our prior set of cross-section analyses, we find some evidence that, post AlexNet, digital/machine learning job postings increase more for firms with PE board members who have also sat on boards of other IT firms. This cross-sectional pattern varies with the number of board members with IT experience.

We contribute to the academic literature in the following ways. First, we contribute to the stream of studies that investigates the roles of capital market participants in the adoption of new technology (e.g., Chen, 2024; Chen and Srinivasan, 2024; Ewens et al., 2018). Research has examined the relationship between public firm investors/securities analysts and digital investments (Chen, 2024; Chen and Srinivasan, 2024). An exception is Ewens et al. (2018), who show that venture capitalists change their investment strategy after a technological shock. We argue that it is important to separately examine PE investor behavior, as it is thought to invest in firms that are less related to technology (e.g., Opler and Titman, 1993). Our contribution is to examine how

sophisticated investors with concentrated ownership (i.e., PE investors) are associated with an increase in digital investments in the private markets.

Second, we contribute to the literature that examines the impact of PE investments (e.g., Agrawal and Tambe, 2016; Bernstein and 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 and Yasuda (2023) for a review of this literature). We demonstrate how PE investors' technology expertise shapes how they add value to their investments. Specifically, we focus on within-establishment technological improvements that may increase the productivity of the portfolio firms. In a similar vein, an important study that relates to our work is by Agrawal and Tambe (2016), who find employees from PE portfolio firms gain transferable, IT-complementary human capital after PE deals. Our work differs from theirs in two ways. First, while their focus is understanding the consequences for the employees' skillsets, ours is firmwide digital technology investments and target firm selection. Second, we further examine whether PE investors reallocate capital in response to technological changes by changing target firm selection and investments into new technology.

We also add to the literature on the determinants of PE investments (Baik et al., 2024; Opler and Titman, 1993; Stafford, 2022) by documenting a change in the PE investment model that has accompanied recent technological advancements. The literature has argued that PE investors (buyout specialists in particular) seek firms/industries with predictable cash flows; our contribution to this literature is to show that PE investors recently have trended toward investing in firms transformable via digital technology and that this approach is associated with favorable outcomes for portfolio firms.

2. 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 none of the datasets captures a complete list of PE transactions (Brown et al., 2015). Furthermore, we strive to identify as many transactions as possible to reduce selection concerns after matching. From these datasets, we focus on leveraged buyouts and growth equity transactions. For Capital IQ data which has more detailed transactions, we select "leveraged buyouts," "management buyout," "going private," or "growth equity" transactions. Any overlapping PE transactions among these datasets are removed.

To obtain information on hirings related to new technology, we gather information from BurningGlass, a database of 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 skills, we use the cluster classification in this dataset to measure a group of skills that relate to machine learning and related technologies, following Goldfarb et al., (2021).

The third dataset we exploit (specifically for PE entry tests) is Aberdeen. This dataset provides detailed information on amounts of IT expenditures and specific types of IT and cloud technologies that firms have invested in. We match this data to our main dataset using the D&B identifier, which describe more in detail in the section below.

3. PE entry and portfolio firm digital investments

3.1 Sample creation and descriptive statistics

To construct our sample to explore whether PE investments relate to increased investments in digital technology, we match the portfolio firms to the D&B data, using (1) website URLs and

(2) a fuzzy name matching algorithm. D&B enables us to obtain basic financial information for private firms in the United States. We also require sales and employee data be available at the year of PE transaction. This procedure yields 15,990 transactions, through the following procedure. 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. Using this sample, we separately match BurningGlass and Aberdeen data to preserve as many portfolio companies as possible. Matching the above sample with BurningGlass data (which contains IT budget information) and performing nearest-neighbor matching within the same two-digit SIC industry yields 6,466 transactions. On the other hand, matching Aberdeen using the same procedure provides 12,601 transactions.[4]

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

Panel B (Panel C) presents the descriptive statistics of the BurningGlass (Aberdeen) sample. The Aberdeen sample contains larger portfolio firms than does the BurningGlass sample, with a 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) than the firms in the Aberdeen

[4] To be more specific on this procedure, 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 two-digit SIC industry. We then select the BurningGlass firm with the closest name for each D&B firm.

sample (0.08). Moreover, 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). In the Aberdeen sample, the mean IT budget is $12.88 million, which is comparable to the statistics reported by He et al. (2022), who report a mean of $11.125 million.

3.2 Research design

3.2.1 Dependent Variables

Using various databases mentioned above, we employ the following variables as dependent variables. We measure the proportion of digital job postings relative to total job postings, pre and post PE investment. Consistent with our approach, extant literature has used job postings as a way to measure the demand for a specific skillset (e.g., Alekseeva et al., 2021; Acemoglu et al., 2022). Specifically, we classify a job posting as digital-related if it 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, and cloud. We examine these postings using the proportion of digital job postings relative to total job postings as the dependent variable. We also measure the natural log of the dollar amount invested in IT, from Aberdeen, which captures the total IT expenditures in each year (following He et al., 2022, and Charoenwong et al., 2024).

3.2.2 Differences-in-differences

One of the most important research design-related concerns in our setting is that it is difficult to rule out endogeneity. First, PE investees may differ inherently from firms that do not receive PE funding. For instance, the portfolio firms may be ones that would be more effective if the PE investors invested in digital technologies. Second, there is a concern that PE investors may time their transactions, selecting firms that are about to make large digital investments, and those

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

To attenuate these concerns, we employ a differences-in-differences strategy to conduct our analyses. To do so, we carefully select, from D&B, a group of control firms that have similar characteristics via propensity score matching. The firms must be in the same industry (SIC two-digit code) and have similar sales and employees measured one year before the treated firm's PE transaction. The covariate balance of the treated and control samples is reported in Table IA1 in the internet appendix.[5] By selecting a group of control firms with similar firm characteristics, we can 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 deal.

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

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

where the dependent variables are different measures of digital investments. $Treat_i$ equals one if the firm 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's PE acquisition 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 growth. To further control for across-firm heterogeneity and time-trends, we also include α_i and α_t as firm and matched-pair year fixed

[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 groups 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 the treated and control groups.

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).

3.3 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 digital job postings pre and post PE transaction 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). The purple (yellow) line represents treated (control) firms. Consistent with our prediction, we observe similar patterns in digital job postings before PE transactions for both types of firms; once a PE invests in a treated firm, we find a sharp increase in treated IT budgets from year *t+1*. The limited differences in pre-trends provide some validation to our matching approach.

Figure 3 Panel B plots the levels of IT investment for treated and control firms instead. Again, this panel presents the mean values for the sample of treated and control firms that have information across the entire event period. The purple (yellow) line represents treated (control) firms. We find an increase in the level of IT investment from *t+1*. Overall, the figures support our prediction that PE transactions lead to higher investment in digital technologies. As in our analysis in Panel A of this table, we also show that there are limited differences in pre-trends.

Table 2 presents the results for our main regression model outlined in Equation (1). Panel A presents the main results, where the dependent variables are the proportion of digital job postings and the natural log of the IT budget. 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 relates to a 1.5 percentage point increase (15% of unconditional

mean) in proportion of digital job postings and 20.5% increase (approximately $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 and reduces the concern that other unobservable characteristics drive our main results. Overall, the main regression results are consistent with our main hypothesis that PE investment leads to increased digital investments of the portfolio companies.

In the Internet Appendix, we run additional tests to gauge whether our main results are robust. In Table IA2, we disaggregate our sample into firms that had low/high IT investments before PE investment, and test whether the results are concentrated around firms that have low investments. The results indicate that the increase in IT budget mainly occurs for firms with low IT investments, which suggests that portfolio firms with low IT infrastructure are experiencing an increase.

Tables IA3 and IA4 decompose the aggregated IT investment and digital job postings into individual items/roles and re-estimate the analysis. In Table IA3, we find that the investment increases across various types of digital expenditures, such as hardware, software, communication, data storage, IT services, and other. In Table IA4, we find the results are strongest for machine learning, data science, BI, and cloud roles.

3.4 Cross-sectional results—portfolio firm/transaction characteristics

3.4.1 AI suitability

Table 3 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) relate to greater digital investments post PE investment, i.e., industries that are more likely to be affected by AI developments. We measure high AIIE industries using the AI exposure measure developed by Felten et al., (2021), which is based on survey responses about AI's potential ability to perform specific tasks, which are then mapped to occupations. The exposure scores at the occupation level are then aggregated at the industry level using industry-level occupation statistics provided by the Bureau of Labor Statistics. Conceptually, this measure captures the exposure of industries and firms to the potential of AI to replace tasks performed by the major occupations of the industries. For instance, professional services, such as accounting and bookkeeping, is classified as an industry with high AI suitability; on the other hand, construction-related industries are defined as low AI suitability industries. We expect that portfolio firms in high AIIE industries are more likely to experience greater increases in digital investments post PE entry. If PE investors increase digital investments in high AIIE portfolio firms, this suggests that the investors focus their digital investments where the opportunities are larger. 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), where $High\ AIIE$ equals one if the industry (the firm) has above-median AI suitability (defined following Felten et al, 2021) and zero otherwise.

The results indicate that portfolio companies in high AIIE industries show stronger measures of digital investment post PE investment, consistent with our expectations. We observe a greater increase in both digital postings and IT budgets for high AIIE industries. Thus, the

evidence supports our prediction that PE investors invest more in digital technologies where the opportunity is the greatest.

3.4.2 Non-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 research documents the benefits of digital transformation in non-IT industries (Babina et al., 2024; Chen and Srinivasan, 2024). To test this claim, we interact IT_d with 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 3 Panel B presents the results. For both dependent variables, while we observe slightly stronger effects for IT portfolio companies, 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 entry. Our results relate to Chen and Srinivasan (2024) and Chen (2024) who find effects for non-IT companies. Moreover, the results in this table reduces the concern that IT portfolio companies entirely drive our results.[6]

3.4.3 Buyout versus growth equity investments

In terms of deal characteristics, we classify PE deals into buyout and growth equity transactions and assess which type of deal exhibits greater growth. Buyouts involve PE investors acquiring a majority stake, which affords them 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 debt of the portfolio firms assume to complete the PE transaction. Consistent with this notion, Jensen (1989) argues that buyouts are an ideal

[6] If IT companies drive our results, the concern would be that PE investors are simply expanding investments into a company's core operations rather than employing new technologies to firms that are less related to technology.

organizational form, as leverage disciplines the firms to make prudent decisions and cut costs. On the other hand, in growth equity deals, PE investors generally invest a minority stake in the portfolio firm. Unlike buyout investors, growth equity investors are more willing to focus on the portfolio firm's growth than maintaining profitability. As in the non-IT portfolio firm test, we add an indicator variable $Growth_d$ as a triple interaction, which equals one if the portfolio firm was involved in a growth equity deal and zero otherwise.

Table 3 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 difference in digital job postings. While some evidence suggests growth equity portfolio companies show stronger increases, the fact that the results continue to hold for buyouts is consistent with the results of Agrawal and Tambe (2016). An interpretation of our results is that investments in digital technology are valuable even for portfolio firms focused on cost cutting, namely buyouts.

3.5 Cross-sectional results—PE investor technology expertise

Exploiting investor-level variation, we test whether the results strengthen for deals where the PE investor has technology expertise. Our prediction is that PE investors with experience investing in the technology industry would be more aggressive in deploying new digital technologies among their other investments. The idea could also explain the mechanisms behind our findings. The board member from the PE investor communicates the most with portfolio firm management. Therefore, that board member's experience can shape the portfolio firm's actions.

Table 4 tests this idea, by regressing the dependent variables on $Treat\ x\ Post\ x\ PortCo\ Digital\ Board$. In Panel A, $PortCo\ Digital\ Board$ equals one if the board member from the PE investor has sat on a board of an IT company and zero otherwise,

information that we obtain from *Pitchbook*. In Panel B, $PortCo\ Digital\ Board$ counts the number of PE board members that sat on IT company boards. The results are significantly stronger for firms with PE board members with IT board experience across both dependent variables. These results demonstrate that PE investors' experience, particularly IT-related, shapes their post-investment behavior (digital spending and hiring). This resonates with the results from Bernstein and Sheen (2016), who find investor experience helps determine post-investment behavior.

3.6 Consequences of digital investments

A natural next question that arises is the consequences of new technology adoption for the portfolio firms. To answer this question, we test whether increases in digital technology are associated with benefits. In Table 5, 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). Specifically, similar to the analyses conducted by Babina et al. (2024), we regress sales/employee/patent growth of the portfolio firms, from one year before PE investment to two years afterward (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 increases in digital job postings and employee growth (column (2)). Conversely, in Panel B, we find that, while the increase in machine learning hiring is positively associated with increased patents (columns (1) and (2)), there is no significant association between IT budgets and innovation. For additional robustness, in Table IA5 we replace the independent variable with an indicator that

equals one if the portfolio firm increased digital investments post PE acquisition, and zero otherwise. The results are qualitatively similar.

We interpret this result consistent with findings of Babina et al. (2024), who show that adoption of digital technologies is associated with enhanced productivity and development of new products and services. Moreover, our results relate to the findings from Hall and Khan (2003) in the sense that PE investors are able to use the new technology to benefit their investments. We conjecture that hiring personnel with experience in machine learning technologies may be more relevant for innovation (Cockburn et al., 2019), while increasing the IT budget could relate more broadly to increased productivity and firm growth.

4. Technological shocks and PE investment behavior

4.1 Introduction of AlexNet

To investigate our second research question, we assess whether PE investors respond to technology breakthroughs by reallocated their capital in different ways. To be specific, we analyze whether PE investors are more likely to target firms with AI suitability after an AI breakthrough. We do so by using the introduction of AlexNet as a setting. In September 2012, AlexNet, as a convolutional neural network, arrived and significantly reduced the error rates of visual recognition (LeCun et al., 2015; Krizhevsky et al., 2017). With AlexNet's introduction (which was a shock to AI's development), our prediction is that PE investors will shift their focus toward investing in firms that have the potential to exploit AI. To proxy for this potential, we measure AI suitability following the Felten et al. (2021) method described before.

4.2 Sample selection and descriptive statistics

We use two main samples to test our research questions. First, to examine whether PE investors shifted their investment behavior, we aggregate the number of PE transactions to form

an industry-year panel. Specifically, we count the annual number of PE transactions for each industry (at the SIC two-digit level). As this sample does not require matching 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 portfolio companies under PE ownership before and after AlexNet's introduction. To do so, we restrict our portfolio company sample (described in section 3.1) to firms that received investment before 2012 (i.e., 2010 and 2011), to ensure that they were PE-owned at the time of AlexNet's introduction. Specifically, we match 1,335 PE transactions to the D&B and BurningGlass data. When we drop firms that do not have sales/employee/job postings information in 2012, this drops to 245 transactions. After nearest-neighbor matching, we arrive at 198 treated transactions with 198 control firms.

We report the mean number of PE transactions for each industry-year in Figure 4. The blue bars (orange bars) represent the average 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 is approximately seven; in 2014, it increases to about nine. 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 that is restricted to existing portfolio companies before and after AlexNet's introduction, described above. Panel A reports the type of PE transactions. There are 157 (117) growth equity (buyout) transactions in the sample, and 56 (217) non-IT (IT) firms. Panel B reports 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 10.52 postings.

4.3 Research design

For both samples, we employ a differences-in-differences strategy. To first analyze whether the number of transactions in high AIIE industries increased post AlexNet, we again user the AI suitability measure used in section 3.4.1. As AlexNet is an AI breakthrough, we anticipate PE investors to increase investments into industries with high AI suitability. Thus, we consider high AIIE industries as treated and the rest as controls. We employ the following Poisson regression model:

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

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 onward, as AlexNet arrived in September 2012. 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 portfolio companies under PE ownership change their investments after AlexNet's introduction, we estimate the following model:

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

where $Y_{i,t}$ is the proportion of machine learning and digital job postings (both scaled by the total number of job postings). The intuition for focusing on machine learning postings is that we expect AlexNet to more directly affect machine learning among various skillsets related to new digital technologies.

4.4 AlexNet and digital targets

Table 6 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) versus (3)), indicating this choice can explain most of the variation in our data. 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. Removing industry fixed effects increases the magnitude to 26.9%. Columns (2) and (4) of the same table present the dynamic effects of the AlexNet test and validate that there are no pre-trends with a similar economic magnitude.

Overall, the evidence suggests that PE investors target firms more frequently that are more likely to be affected by AI after a breakthrough in technology. This resonates with the notion that PE investors are sensitive to technological breakthroughs and respond by allocating capital to different types of firms.

4.5 AlexNet and existing portfolio companies

We examine whether PE portfolio companies invest more into AI-related technology post AlexNet in Table 8 by estimating equation (3). Panel A columns (1) and (2) show that, post AlexNet, PE portfolio companies in high AIIE industries exhibit a significant increase of 3.6% (3.1% with firm fixed effects) in machine learning job postings. Similarly, columns (3) and (4) demonstrate a significant increase in digital job postings after AlexNet as well. The economic magnitude is smaller, at around 0.5% increase for both specifications. This is consistent with our expectation that AlexNet has the greatest effect on AI-related job demand such as machine learning compared to other digital skillsets.

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 the attractiveness of the high AI suitability industries drives our results. The economic magnitude is similar to the magnitude reported in Panel A.

4.6 PE entry and digital technology—before and after AlexNet

Recall that, in section 3, we find that PE entry into portfolio companies is associated with greater IT investments. We also test whether this association changes pre and post AlexNet. To do so, we restrict the main sample in section 3.1 to high AI suitability portfolio companies that are active pre and post AlexNet and re-estimate equation (1). In Panel A (Panel B), we use machine learning (digital) job postings as the dependent variable.

Table 9 Panel A shows that the relationship between PE entry and machine learning job postings is much weaker before AlexNet. Specifically, column (1) reports a statistically insignificant coefficient on $Treat\ x\ Post$, when we restrict our sample to the years beforehand. On the other hand, column (2) reports a positive and meaningful coefficient, and it is significantly different compared to that of column (1). Similarly, Panel B reports the same regressions but using the proportion of digital job postings as the dependent variable. 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 the investment behavior of their portfolio companies when technology advances meaningfully.

4.7 Cross-sectional results—investor expertise

As in section 3.5, we examine whether the effects strengthen for portfolio companies owned by PE investors with new technology expertise. Using the portfolio firm-level sample used in section 4.6, in Table 10, we examine whether the observed effect on existing portfolio firms

strengthens for firms with PE board members with IT firm board experience, as in Table 4. Specifically, we study the 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 board and zero otherwise or as the count (in Panel B) of the board members having IT board experience. We interact this with $Treat_i\ x\ Post_{i,t}$ and estimate equation (3).

Consistent with our expectations, we find that portfolio companies in high AI suitability industries and with board members with IT experience exhibit stronger relationships with digital investments. Specifically, Panel A column (2) shows a significant relationship with the variable $Treat\ x\ Post\ x\ Portco\ Digital\ Board$. Moreover, Panel B also shows significant relationships for both columns. Thus, our results collectively suggest that exposure to new technology is associated with a greater increase in new technology investments.

5. Conclusion

We find that PE investors bring new technology to their portfolio firms by increasing digital technology investment in those firms, selecting target firms more suited for new technologies, and increasing investment in new technology for existing portfolio firms post technological advancement. Notably, we find highlighted effects when the PE investor has expertise on new technology. We also find that investment in new technology is associated with favorable outcomes, such as firm growth and innovation.

We contribute to academic literature in three ways. First, we contribute to the digital transformation literature by demonstrating that private investors can help reduce the digital investment gap between public and private firms. Second, we complement the literature on the impact of private equity transactions. We show that PE investors facilitate digital transformation in their portfolio companies to accelerate their growth and emphasize the role of investor expertise

in adding value to portfolio firms. Finally, we show that the determinants of PE investing are shifting toward firms that are transformable using digital technology.

Overall, our analysis finds that PE investors matter in new technology adoption, particularly, for the new digital technologies, such as analytics, big data and AI, that have emerged in recent years.

References

Acemoglu, D., Autor, D., Hazell, J. and P. Restropo (2022). AI and Jobs: Evidence from Online Vacancies, *Journal of Labor Economics 40*(51).

Acharya V. and Z. Xu (2017). Financial dependence and innovation: the case of public versus private firms. *Journal of Financial Economics 124*(2):223–43.

Alekseeva, L., J. Azar, M. Giné, S. Samila, and B. Taska. (2021). The demand for AI skills in the labor market. *Labour Economics 71* (August): 102002.

Aggarwal V. A., and D. H. Hsu (2014) Entrepreneurial exits and innovation. *Management Science 60*(4):867–87.

Aghion, P., and Howitt, P. (1992). A model of growth through creative destruction. *Econometrica 60*(2): 323-351.

Agrawal, A., and Tambe, P.. (2016). Private equity and workers' career paths: The role of technological change. *Review of Financial Studies 29*(9), 2455-2489.

Asker J., Farre-Mensa J., Ljungqvist A. (2015). Corporate investment and stock market listing: A puzzle? *Review Financial Studies 28*(2):342–90.

Babina, T., A. Fedyk, A. X. He, and J. Hodson (2024). Artificial Intelligence, Firm Growth, and Industry Concentration. *Journal of Financial Economics (Forthcoming).*

Baik, B.K., Berfeld, N., and R.S. Verdi (2024). Do public financial statements influence venture capital and private equity financing? *The Accounting Review* (Forthcoming).

Baker, A.C., Larker, D.F., and C.C.Y. Wang (2022). How much should we trust staggered difference-in-differences estimates? *Journal of Financial Economics 144(2)*: 370-395.

Bernstein, S. (2015). Does going public affect innovation? *Journal of Finance 70*(4):1365-403.

Bernstein S. (2022). The Effects of Public and Private Equity Markets on Firm Behavior. *Annual Review of Financial Economics 14*(1).

Bernstein S., Giroud X., Townsend R.R. (2016). The impact of venture capital monitoring. *Journal of Finance 71*(4):1591–622.

Bernstein S. and A. Sheen (2016). The operational consequences of private equity buyouts: evidence from the restaurant industry. *Review of Financial Studies 29*(9):2387–418.

Bresnahan, T. F. and S. M. Greenstein (1996). Technical progress and co-invention in computing and in the uses of computers. In: *Brookings Papers on Economic Activity. Microeconomics*, pp. 1–78.

Bresnahan, T. F., Brynjolfsson, E. and L. M. Hitt (2002). Information technology, workplace organization, and the demand for skilled labor: firm-level evidence *Quarterly Journal of Economics 117*(1), 339–376.

Bresnahan, T. F., R. M. Henderson, and S. Greenstein (2012) Schumpeterian Competition and Diseconomies of Scope: Illustrations from the Histories of Microsoft and IBM. In: *The Rate and Direction of Inventive Activity Revisited*, edited by J. Lerner and S. Stern. National Bureau of Economic Research.

Brown, G.W., Harris, R.S., Jenkinson, T., Kaplan, S.N. and Robinson, D.T. (2015). What do different commercial data sets tell us about private equity performance? *SSRN Working Paper.*

Bloom, N., Sadun, R. and J. Van Reenen. (2012). Americans Do IT Better: US Multinationals and the Productivity Miracle. *American Economic Review 102*(1) (February): 167–201.

Boucly, Q., Sraer, D., Thesmar, D. (2011). Growth LBOs. *Journal of Financial Economics 102*(2): 432-453.

Brynjolfsson, E., and L. Hitt (1996). Paradox Lost? Firm-Level Evidence on the Returns to Information Systems Spending. *Management Science 42*(4) (April): 541–558.

Brynjolfsson, E., and M. D. Smith (2000). Frictionless Commerce? A Comparison of Internet and Conventional Retailers. *Management Science 46*(4) (April): 563–585.

Brynjolfsson, E., Rock, D. and C. Syverson (2017). Artificial Intelligence and the Modern Productivity Paradox: A Clash of Expectations and Statistics. *NBER Working Paper 24001.*

Brynjolfsson, E., Rock, D. and C. Syverson (2021) The productivity J-curve: how intangibles complement general purpose technologies. *American Economic Journal: Macroeconomics 13*(1), 333–372.

Calvino, F., Criscuolo, C., Marcolin, L. and M. Squicciarini (2018), A Taxonomy of Digital Intensive Sectors, *OECD Report.*

Cao, R., and M. Iansiti (2022). Digital transformation, data architecture, and legacy systems. *Journal of Digital Economy 1*(1), 1-19.

Charoenwong, B., Kowaleski, Z., Kwan A. and A. Sutherland (2024), RegTech, *Journal of Financial Economics* (Forthcoming).

Chen, W. X. (2024), Analyst Focus on AI and Corporate Demand for AI Technologies, *SSRN Working Paper.*

Chen W. X. and S. Srinivasan (2024), Going Digital: Implications for Firm Value and Performance. *Review of Accounting Studies 29*, 1619-1665.

Cockburn, I., R. Henderson, and S. Stern (2018). "The Impact of Artificial Intelligence on Innovation." *NBER Working Paper 24449*.

Cohn, J. B., Mills L. F. and E. M. Towery (2014). The evolution of capital structure and operating performance after leveraged buyouts: Evidence from U.S. corporate tax returns, *Journal of Financial Economics 111*(2), 469-494.

Cohn, J. B., Liu, Z., and M. I. Wardlaw. (2022). Count (and count-like) data in finance. *Journal of Financial Economics 146(2):* 529-551.

Davis, S.J., Haltiwanger, J., Handley, K., Lerner, J., Miranda, J. (2014). Private equity, jobs, and productivity. *American Economic Review 104*(12): 3956-3990.

EY (2023). As private equity matures, what's the best path forward for CFOs as they enter a new era?. *2023 Global Private Equity Survey.*

Felten, E., Raj, M. and R. Seamans (2021). Occupational, industry, and geographic exposure to artificial intelligence: A novel dataset and its potential uses, *Strategy Management Journal 42*(12), 2195-2217.

Gao H., Hsu P. H. and K. Li (2018). Innovation strategy of private firms. *Journal of Financial Quantitative Analysis 53*(1):1–32.

Goldfarb, A.,Taska, B. and F. Teodoridis (2022). Could Machine Learning Be a General-Purpose Technology? Evidence from Online Job Postings. *NBER Working Paper 29767*.

Guo, S., Hotchkiss, E. and W. Song (2011), Do Buyouts (Still) Create Value? *Journal of Finance 64*(2): 479-517.

Hall, B.H., Khan, B. (2003). Adoption of new technology. NBER Working Paper No. 9730.

He, Z., Jiang S., Xu, D. and X, Yin (2022), Investing in Lending Technology: IT Spending in Banking. NBER Working Paper No. 30403.

Henderson, R. M. and K. B. Clark (1990). Architectural innovation: the reconfiguration of existing product technologies and the failure of established firms. *Administrative Science Quarterly 9*(30): 9-30.

Jensen, M. (1989). The Eclipse of the Public Corporation, *Harvard Business Review 67*, 61–74.

KPMG (2018). The Digital Transformation Imperative, *KPMG Whitepaper.*

Kaplan (1989). The Effects of Management Buyouts on Operating Performance and Value, *Journal of Financial Economics 24*: 217-254.

Kogan, L., Papanikolaou, D., Seru, A., Stoffman, N. (2017). Technological innovation, resource allocation, and growth. *Quarterly Journal of Economics 132*(2): 665-712.

Krizhevsky, A., Sutskever, I., and G. E. Hinton. (2017). ImageNet classification with deep convolutional neural networks. *Communications of the ACM 60(6):* 84-90.

Lakhani, K., and M. Iansiti (2020). Competing in the Age of AI: Strategy and Leadership When Algorithms and Networks Run the World. *Harvard Business School Press.*

LeCun, Y., Bengio, Y., and G.E. Hinton. (2015). Deep learning. *Nature 521:* 436-444.

Lerner, J., Sorensen, M. and P. Strömberg (2011). Private equity and long-run investment: the case of innovation. *Journal of Finance 66*(2): 445–477.

Matthews, G., Bye, M., and J. Howland (2009). Operational improvement: The key to value creation in private equity. *Journal of Applied Corporate Finance 21(3)*: 21-27.

McKinsey (2023). *Private equity investments in tech services: Three considerations.*

Opler T. and D. Titman (1993), The Determinants of Leveraged Buyout Activity: Free Cash Flow vs. Financial Distress Costs. *Journal of Finance 48*(5): 1985-1999

Pagano, M., Panetta, F. and L. Zingales (1998). Why do companies go public? An empirical analysis. *Journal of Finance 53*(1): 27–64.

Romer, P.M. (1990). Endogenous technological change. *Journal of Political Economy 98*(5): S71-S102.

Saunders A. and S. Steffen (2011). The costs of being private: evidence from the loan market. *Review of Financial Studies 24*(12):4091–122.

Sorensen, M., Yasuda, A. (2023). The stakeholder impact of private equity investments. *Handbook of the Economics of Corporate Finance 1*(1): 299-341.

Stafford, E. (2022). Replicating private equity investing with value investing, homemade leverage, and hold-to-maturity accounting. *Review of Financial Studies 35(1):* 299-342.

Tambe, P., Hitt, L. M., Rock, D. and E. Brynjolfsson (2020). Digital Capital and Superstar Firms. *NBER Working Paper 28285.*

UBS (2019). UBS Evidence Lab inside: IT survey suggests size matters; could consolidation be a result?, *UBS Global Research Report*

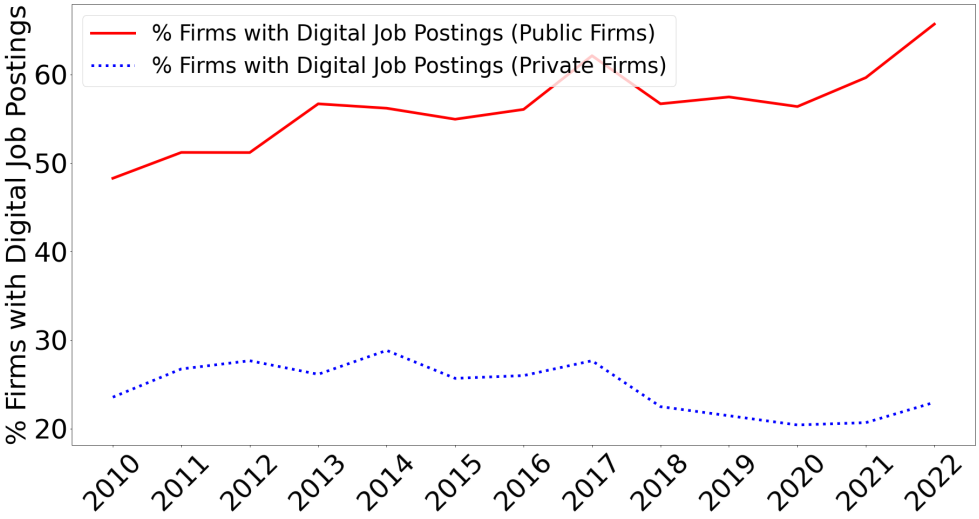
West Monroe (2019), "Digital at the speed of private equity", *West Monroe Partners Research Note.*

Zolas, N., Kroff, Z., Brynjolfsson, E., McElheran, K., Beede, D. N., Buffington, C., Nathan, G., Foster, L., Dinlersoz, E. (2020). Advanced Technologies Adoption and Use by US Firms: Evidence from the Annual Business Survey. *NBER Working Paper 28290.*

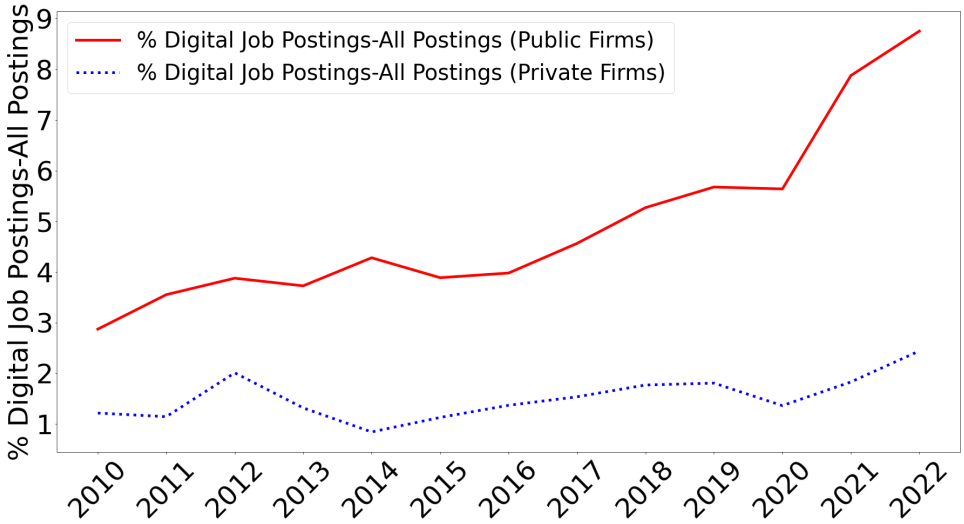
Appendix A: Variable Definitions

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

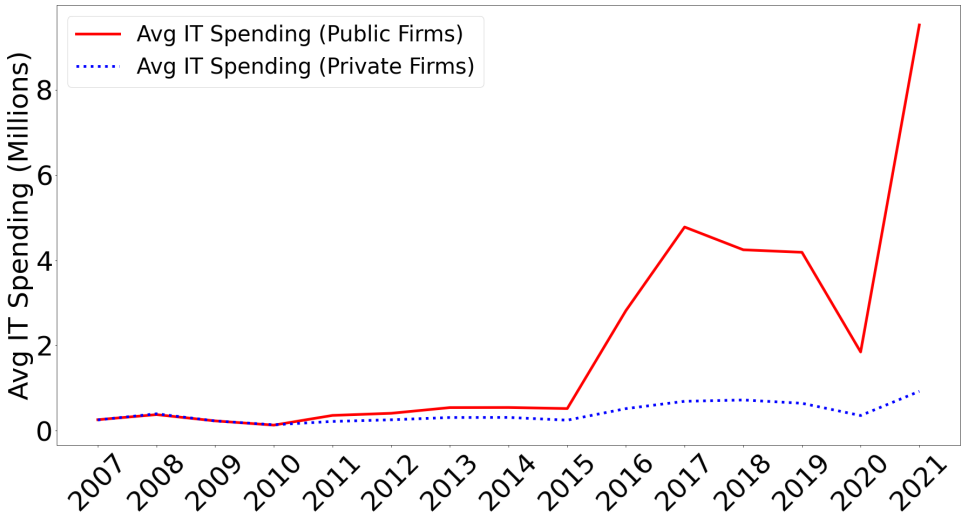
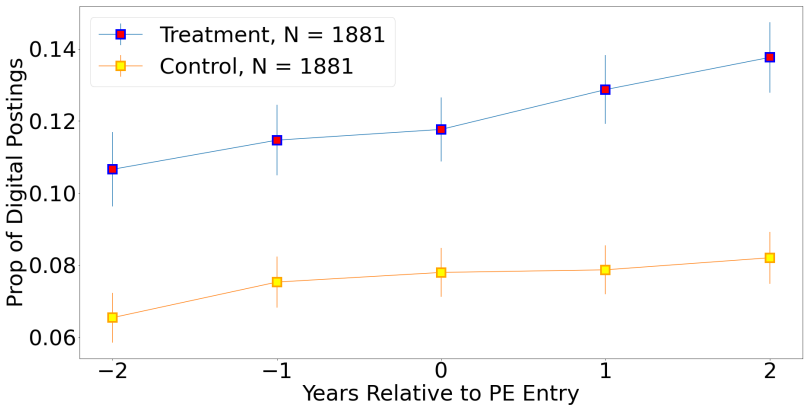
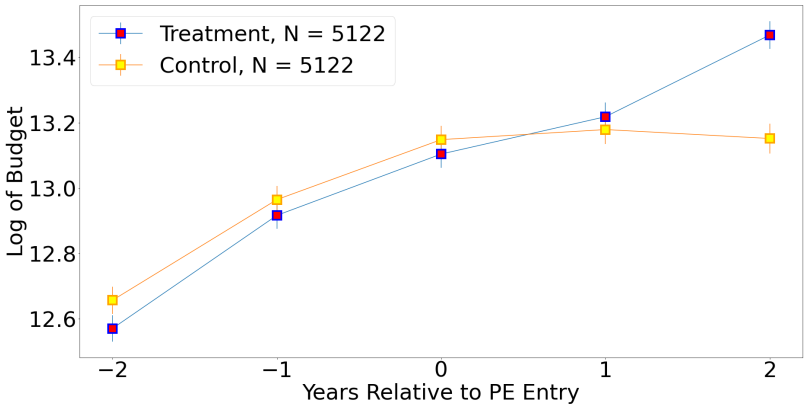


Figure 2: Time-series Distribution of Average IT Spending for Public and Private Companies



(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.

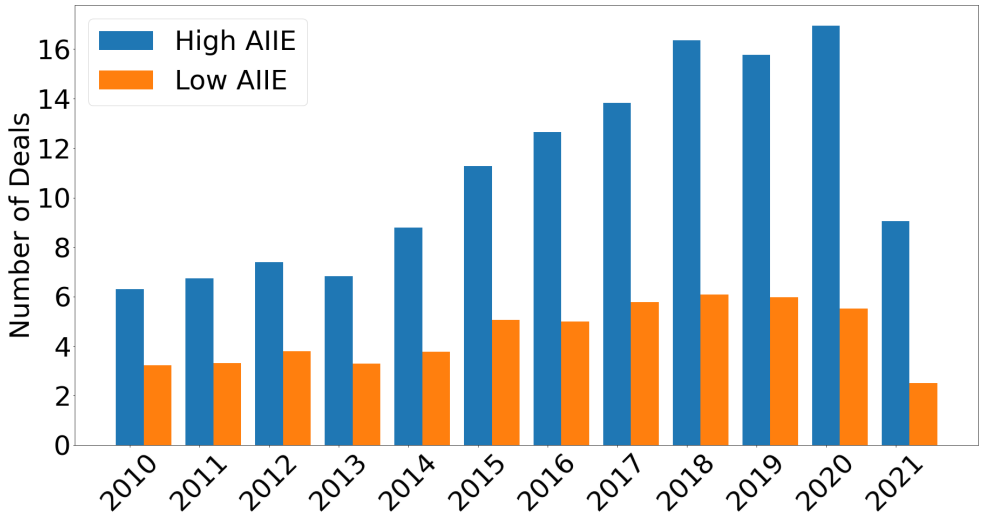


Figure 4: Time-series Distribution of Average Number of Deals in Industries with High or Low AI Industry Exposure (AIIE)

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 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: 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 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 4: 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 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 5: 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 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 6: 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 AIIE$_j$ ×Post(AlexNet)$_{y>2012}$	0.269***	0.282***	0.197**	0.191***
	(0.081)	(0.100)	(0.094)	(0.059)
High AIIE$_j$ ×Post(AlexNet)$_{y=2011}$		0.041		0.077
		(0.053)		(0.072)
High AIIE$_j$ ×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 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 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 9: 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 10: 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 Investment and 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 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 IA.3: 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 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.4: 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 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.5: 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 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