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Abstract

We study the role which private equity (PE) plays in digital transformation. We find that PE investment is associated with greater investments into portfolio firm's digital technologies, as measured by IT expenditures and the hiring demand for AI skills. This relationship is more pronounced for growth equity investments, and portfolio firms invested by PE investors with greater exposure and expertise in digital technology. Consistent with the broad range of applications for digital technologies, non-IT portfolio companies also significantly increase their digital investments post PE investment. Lastly, we study the potential benefits from digital investments, and find that an increase in these investments after PE entry, is associated with stronger portfolio firm sales/employee growth and innovation. Overall, our results highlight that PE investors increasingly drive value creation using digital technologies in their portfolio companies.

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

JEL Codes: G24; G32; O33

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1. Introduction

Private equity (PE) investment in the technology sector has grown more than six-fold for the past 10 years. According to McKinsey (2023), the tech sector globally attracted $675 billion from PE investors, up from $100 billion in 2012. This trend is in contrast to the "traditional" PE model, where these investors are believed to invest in industries with stable cash flows (Opler and Titman, 1993), such as manufacturing, retail, and industrials. Furthermore, as competition intensifies in the PE industry from influx of capital, the exposure to new technology through investments in the technology sector can shape how the PE investors create value in their portfolio firms. PE investors can also leverage technology as a way to enhance operational efficiency in their portfolio companies, by deploying and investing in new technologies that may create synergies with the portfolio company. Against this backdrop, we investigate the role of PE investors in the portfolio company's digital transformation, and its consequences.

We hypothesize that PE investment is associated with digital transformation, for two reasons. First, academic studies show that PE investments are linked to better operational efficiency and productivity. The investors also view the enhancement of operational efficiency of their portfolio firms as the most important value-add to their investments (Gompers et al., 2016). Second, as digital transformation is associated with various financial and non-financial benefits (e.g., Agrawal and Tambe, 2016; Babina et al., 2022; Chen and Srinivasan, 2022; Cockburn et al., 2018), PE investors may invest in digital infrastructure/personnel, to enhance portfolio firm performance. In fact, in a recent survey of PE investors, approximately half of the respondents answered that they deploy new technologies to prevent erosion in portfolio firm margins (EY, 2023). The new technologies also can become more relevant as the competition in the PE industry intensifies.

On the other hand, there are reasons to believe PE investors may not engage in digital investments. First, PE investors may engage in less digital investments as PE investors consider cost cutting as one of the most important value-adds to their portfolio firms (Gompers et al., 2016; Sorensen and Yasuda, 2023). PE firms may choose not to invest in digital systems and infrastructure if the primary focus is to reduce portfolio firm costs. Similarly, Matthews et al., (2009) argue that investing in portfolio firm IT systems is a high-risk/high-reward type project, which takes significant upfront costs. Second, as these investments are closely tied to commercialization activities (the application of existing digital technologies). Prior work has shown that PE firms tend to be associated with less commercialization-related innovation compared to public firms (Bernstein, 2015; Gao et al., 2018), as commercialization activities tend to be more suited for public markets. Second, investing in digital technology bears high idiosyncratic risk, such as backlash from the workforce (Furman and Seamans, 2019) due to displacement of labor (Acemoglu and Restropo, 2019), or cybersecurity risk (e.g., Huang and Wang, 2020; Kamiya et al., 2020). Digital investments may not necessarily lead to better firm outcomes, or enhanced productivity. PE investors may not prefer to invest in risky projects with high uncertainty.

To test our hypothesis, we create a unique dataset that combines information on digital investments and PE transactions. First, we focus on the Aberdeen dataset, which provides information on the investment of new technologies. The dataset contains information on firm-year level digital technology-related infrastructure, such as hardware, software, data storage, IT services, IT staff, and telecommunications. Second, we focus on job posting data provided by BurningGlass Technologies, which covers [comprehensive] information on the near universe of online job postings. The dataset contains information on the required skill sets for implementing digital technologies, which serves as a good proxy of corporate demand for digital personnel. We match these datasets to a list of buyout transactions from 2010-2021, obtained from Capital IQ, and establishment-level sales and employees data from Dun and Bradstreet (D&B). Our unit of observations is at the portfolio firm-year level. Our research design follows a generalized and stacked differences-in-differences strategy, where the treated firms are the ones that undergo a PE transaction.[1] The group of control firms are obtained from D&B, and are firms that are in the same industry, with similar sales, employees, and digital investment at the year of the treated firm's PE transaction. Our main dependent variables are the dollar amount of IT budget (from the Aberdeen dataset following He et al., 2022; Charoenwong et al., 2024), indicator and the number of AI-related job postings (following the job postings skills list in Alekseeva et al., 2021).

We first analyze whether PE investors respond to the developments in digital technology by altering their choice of investments. In particular, we examine whether the introduction of AlexNet, an event considered to be a breakthrough in the field of AI (LeCun et al., 2015; Krizhevsky et al., 2017), influenced PE investors to invest in firms that are in industries with high AI potential (from Felten et al., 2021), i.e., industries with occupations that are expected to be more affected by the introduction of AI. Consistent with the argument that PE investors began to shift their investment preferences since the breakthrough in AI technology, we find that firms with high AI potential were more likely to be targeted by PE investors after the introduction of AlexNet. The results are robust to controlling for key target firm characteristics, such as size and operating performance, measured at the transaction period. Furthermore, we verify that firms

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

with high AI potential are associated with stronger positive changes in IT budget and AI job postings.

As our main analysis, we examine whether portfolio companies invest in digital technologies post PE investment. Consistent with our hypothesis, we find a statistically significant increase in IT-related investments in our main analysis. Economically, the coefficients indicate a 14% increase in portfolio firm IT budget, 2.8% increase in the probability of AI job postings, and 3.8% increase in the number of AI job postings. Our analyses are robust to poisson regressions (specifically for AI postings), which alleviates the concern that our results are driven by biased estimates from using logged one plus count values as dependent variables (Cohn et al., 2022). The main results are consistent with our hypothesis that PE investors expand the portfolio firm's investments into digital technologies. In addition to the main regression, we validate our main results by demonstrating the absence of pre-trends through dynamic regressions. Moreover, we also show that our IT results are driven by portfolio firms with high IT investments relative to industry peers, before PE investment. Thus overall, we find consistent evidence that PE investors are associated with the investments of new digital technologies in their portfolio companies.

Building on the idea that there are multiple facets of a digital strategy, we examine (i) the specific IT investments that investors focus on, and (ii) whether PE investors use alternative digital investment approaches in addition to the strategies mentioned above. Regarding (i), we analyze whether the IT budget increase is concentrated around certain areas, i.e., hardware, software, and communications. We find a similar magnitude of increase for all types of IT budgets. Regarding (ii), we argue that the portfolio firms can acquire IT companies to integrate their core technologies into the portfolio firms to enhance efficiency. Furthermore, they can apply cutting-edge technologies to their company websites that can enhance analytics of the portfolio firm website visitors. We investigate this idea by exploiting the number of acquisitions the portfolio firm makes into IT firms, and the number of technologies applied to the portfolio company websites, as dependent variables. The consistent results using different measures suggest that PE investors apply various techniques (i.e., increase IT-related spending, hire more AI personnel, acquire technology companies, and apply more technologies to their websites) as means to increase IT investments.

Next, we present cross-sectional tests using different measures of digital expertise at the PE investor level. These tests also help us further understand potential mechanisms of our effects. Our conjecture is that PE investors with more technology-related exposure would be more likely to invest in digital technologies, because they could be more familiar with cutting-edge technologies that may be applicable to their investments and they may have more tools to integrate digital technologies into their portfolio firms. Consistent with this notion, we find stronger results for portfolio firms invested by PE investors with technology-related investment experience. Specifically, we show that the results are stronger for portfolio firms invested by PE investors who had at least one prior investment in IT firms. In addition, the results are also pronounced for PE investors that have employees with digital/data related expertise or AI personnel in their PE firm, and for portfolio firms with board members from PE investors that have sat on boards of IT firms. Collectively, the results demonstrate that PE investors that exhibit greater experience and expertise in digital technologies, are associated with greater digital technology adoption in their new portfolio company investments. In other words, we find suggestive evidence that PE investors with greater exposure to digital technology, through their previous IT investment experience, the existence of AI personnel, and board members with IT board experience, are more likely to encourage digital investment in their portfolio companies. Overall, the results are consistent with the findings from Bernstein and Sheen (2016) that operational improvements from PE portfolio firms are mainly driven by investors with prior industry expertise.

Third, we exploit the characteristics of the PE transactions and examine whether certain characteristics drive our results. To investigate this argument, we test whether the main effects hold when we additionally interact with the IT firm indicator. While we do find that the increase is significantly larger for most digital outcomes for IT portfolio firms, the main effects indicate that the results still hold for non-IT portfolio firms. For instance, we do not observe a statistically significant difference with respect to the increase in IT expenses for non-IT portfolio firms than for IT portfolio firms. The results mitigate the concern that the results may be driven only by portfolio firms in the IT industry. The results are consistent with the argument that PE investors invest in these technologies even to non-IT firms.

In addition, we find that our results are generally stronger for growth equity transactions than for buyouts. Specifically, growth equity transactions show stronger increase in both IT budget and AI job postings. This finding is consistent with the notion that buyouts focus on cutting costs of their portfolio firms (Sorensen and Yasuda, 2023), whereas growth equity deals focus more on expanding the portfolio firm’s business. To do so, investing in digital technologies can be an efficient way to achieve faster growth of their investments.

In our final set of tests, we examine the consequences of the digital transformation. Prior evidence suggests that the adoption and integration of digital technologies is associated with enhanced productivity, development of new products/services (Babina et al., 2022), and improving innovation processes (Cockburn et al., 2018). We test these claims in a PE-backed portfolio company setting. In particular, we examine whether digital transformation at the portfolio firm level is associated with future sales and employee growth, and find that portfolio firms that increase their investments into digital technology, after PE entry, achieve faster sales and employee growth. The results are qualitatively similar when we restrict our portfolio firms to non-IT firms, which mitigates the concern that the consequences may simply be a result from IT firms making additional investments to their core business.

Another potential benefit of digitalization in portfolio firms is innovation. Prior research argues that advanced digital technologies such as artificial intelligence, could have an impact on innovation by improving the R&D process (Cockburn et al., 2018), and we test whether that is also the case for PE investments. To test the idea, we obtain patent data from the USPTO database and count the number of patents, as a proxy for innovation activity. Similar to the sales test discussed above, we analyze and find that increases in AI job postings post PE investment are associated with stronger likelihood of obtaining a patent, and with an increase in the number of patents. The result is again robust to the analysis of only Non-IT firms. On the other hand, we do not observe an increase in innovation when IT budgets increase post PE investment. One reconciliation of the result is that the AI 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 contribute to the academic literature in the following ways. First, we contribute to the PE literature that examines the impact of PE investments (e.g., Agrawal and Tambe, 2016; Bernstein and Sheen, 2016; Boucly, Sraer, and Thesmar, 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 on this research question), by demonstrating how PE investors' recent exposure to new technology shapes the way they add value to their investments. More specifically, we focus on within-establishment technological improvements that may help the productivity of the portfolio firms. In a similar vein, an important study that is related to our work is, Agrawal and Tambe (2016), who find employees from portfolio firms that undergo IT transformation gain transferable, IT-complementary human capital after their firm is acquired by PE investors. Notably, the focus of their study is on the consequences of the portfolio firm employees. In contrast, we focus on the firmwide digital technology investments made by these portfolio firms after PE transactions, such as hardware, software, and the specific skill sets required to solicit digital technology personnel.

Relatedly, we add to the literature that studies the determinants of PE investments (Baik et al., 2024; Opler and Titman, 1993; Stafford, 2022), by documenting a change in PE investment model from the rapid technological advancement. Previous literature has found and assumed that PE investors (buyout in particular) look for firms/industries with stable and predictable cash flows; our innovation is that PE investors recently have trended towards investing in firms that are transformable through various investments in digital technology, and that this value creation strategy is associated with favorable outcomes for the portfolio firm.

Finally, we contribute to a recent group of studies that investigates the roles that capital market participants play in digital transformation. Prior work has examined the relationship between public firm investors and digital investments (Chen and Srinivasan, 2023), and have also examined the relationships between key capital market intermediaries, such as securities analysts, and AI technologies (Chen, 2023). Our contribution relative to these studies, is to examine how sophisticated investors with concentrated ownership (i.e., PE investors) are associated with increase in digital investments, in a private firm setting.

2. Data and descriptive statistics

2.1 Data and sample selection

We obtain a sample of PE transactions completed from 2010 to 2021 for firms located in the United States, from Capital IQ. We identify 35,272 PE transactions. Next, 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 drop transactions without any matches in the data.

Using this sample, we further match several datasets to obtain more information on digital investments. First, we obtain information on the investment in the infrastructure (the backend) of digital technologies through surveys of IT spending and IT architecture, provided by the Aberdeen dataset. This data provides detailed information on the amounts of IT expenditures, and specific types of IT and cloud technologies that organizations have invested in. Second, we match the BurningGlass data set by fuzzy matching and manual verification. This dataset covers the near-universe of online job postings and has been used to measure corporate job postings on software and AI-related technologies (Babina et al 2022, Acemoglu et al., 2022). To measure AI-specific skills, we use the BurningGlass dataset to measure a cluster of skills that relate to AI technologies (Alekseeva et al., 2021).

2.2 Descriptive statistics

Table 1 shows the summary statistics of our samples. Panel A reports the deal and portfolio firm types of our sample. The composition of deal types is similar between the two samples; the Aberdeen sample has 5,940 and 1,541 growth equity and buyout deals, respectively, while the BurningGlass sample consists of 3,619 and 1,038 growth equity and buyout deals, respectively. In terms of portfolio firm characteristics, the Aberdeen sample consists of 5,041 non-IT firms and 2,440 IT firms; the BurningGlass sample has 2,930 and 1,726 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 219.33 (138.92) mean number of employees and $36.77 million ($19.11 million) in sales. Firms in the BurningGlass sample show a higher sales growth (0.17) than the firms in the Aberdeen Sample (0.10). In the Aberdeen sample, the mean IT budget is $13.23 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 of AI job postings (indicator of AI job posting) is 2.36 (0.22).

Figure 1 presents the number of PE transactions each year. Panel A shows the number of all deals from 2000 to July 2023;[2] Panel B shows the number of IT transactions for the same period. Blue bars (orange bars) indicate buyout (growth equity) transactions. One observation from both panels is the jump in the number of growth equity transactions in 2014. We observe a similar pattern for IT-related deals in Panel B.

Figure 2 shows the median deal size across the time series. Specifically, we present median deal values for top 100 PE investors that made the most changes in IT spending (blue bar; "top 100 PE investors") and deal values for the rest of the PE investors (orange bar). Panels A, B, and C present the deal values for all deals, buyout deals, and growth equity deals, respectively. Several observations emerge from these figures. For most years, we find higher deal values for PE transactions that involve top 100 PE investors than for transactions from the rest of the PE investors. Second, the deal values increase with time, especially years after COVID-19

[2] Note that we present the number of deals from 2000 to 2023 for illustrative purposes; our sample period is from 2010 to 2021).

outbreak (i.e., year 2021 and 2022). This is consistent with the favorable interest rate environment and capital inflows across all asset classes during this period.

2.3 The shift in PE target characteristics from advances in digital technology

We first investigate whether PE investors alter their targeted portfolio firms once there is a breakthrough in digital technology. The analysis can provide us with preliminary evidence that PE investors do respond to technological advancements. To be specific, we analyze whether the PE investors are more likely to target firms with 'AI-potential' after an event which triggered a substantial development in the field of AI, using the introduction of AlexNet as a setting. In September 2012, AlexNet was introduced, a convolutional neural network which significantly enhanced the error rates of visual recognition. With the introduction of AlexNet (which is a shock to AI's technological development), our prediction is that PE investors would have focused on investing into firms that have potential to be affected by the advent of AI. We call these firms with a high 'AI-potential'.

We measure the firms with a high AI-potential using the measure developed by Felten et al., (2021). The measure is based on surveyed responses of AI's potential ability to perform specific tasks, which are then mapped to occupations, and further aggregated at the industry-level using industry-level occupation statistics provided by the Bureau of Labour Statistics. Thus conceptually, this measure captures the exposure of industries to the potential of AI to replace tasks performed by the occupations of the industries. We expect the PE investors to increase their investments into firms with higher AI potential post AlexNet.

Figure 3 reports the number of PE deals from 2000-2021. The blue and orange bars represent the number of PE deals that target high and low AI potential (AI industry exposure, AIIE), respectively. We find a sharp increase in completed PE deals that target firms with high

AI potential from 2014, consistent with our prediction that the development in AI has altered PE firms to invest in companies with high AI potential.[3]

Table 2 Panel A reports the regressions testing this idea. In columns (1) and (2), we regress the indicator Post(AlexNet), which equals one if the deal completion year is after AlexNet introduction (i.e., from 2013), on the independent variable High AI Potential, which equals one if the target company is in an industry with high AI potential (defined by Felten et al., 2021), and zero otherwise. Column (2) includes target firm characteristics, obtained from Capital IQ. We find that target companies with high AI potential are 9.7%p more likely to be invested by a PE firm post AlexNet. In columns (3) and (4), where we use years relative to AlexNet (2012) as the dependent variable, we show that firms with high AI potential are likely to be invested 1.081 years later, again consistent with our prediction.

Panel B of the same table validates whether portfolio firms with high AI potential are related to stronger digital investments post PE investment. Specifically, in columns (1) and (2), we regress the indicators High IT Budget (AI Job Postings) Change, which equals one if the portfolio firm is classified as a firm that increases IT budget (AI Job Postings) more than the median, and zero otherwise, respectively. Year fixed effects are included and standard errors are clustered by industry. We find a stronger likelihood of high AI potential portfolio firms increasing both IT budget and AI job postings.

3. Research Design

3.1 Dependent variables

[3] Note that AlexNet was first introduced in September 2012, and a potential question would be why we do not observe a notable increase in 2013. We argue that PE investors would take time to identify, bid, and close their investments, and therefore may more than a year to observe a significant increase.

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; Charoenwong et al 2024).[4] Second, we use BurningGlass to measure the number of AI-related job postings pre and post PE investment.[5] Specifically, following Alekseeva et al., (2021), we classify a job posting to be AI-related if the posting lists at least one of the following words as required skillsets: artificial intelligence, machine vision, deep learning, or speech recognition.[6]

3.2 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, the portfolio firms may be firms that would be effective if the PE investors invested in digital technologies. Second, there is a concern that PE investors may have 'timed' the transaction period correctly, and IT investment would have increased regardless of a PE transaction. 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 differences-in-differences strategy to conduct our analyses. To do so, we carefully select a list of control firms that have similar firm characteristics and industries via propensity score matching, which is obtained from Dun and Bradstreet, by requiring the firms to be in the same industry (SIC two-digit code) and have

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[4] We first measure the IT budget at the site-year-level and aggregate at the firm-year-level.
[5] 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).
[6] For the specific skills see the Appendix in Alekseeva et al (2021).

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.[7] By selecting a group of control firms with similar firm characteristics, we are able to reduce the concerns mentioned above.

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 explained in section 3.1; $Treat_i$ 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 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. Main Results

4.1 Figures

[7] 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, 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.

We first graphically analyze whether there is a significant increase in digital investments post PE transactions. Figure 4, Panel A presents the levels of IT budgets 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).[8] Purple (yellow) line represents treated (control) firms. Consistent with our prediction, we observe a similar pre-trend before PE transaction for the treated and control firms; once the PE invests in the treated firm, we find a sharp increase in IT budgets from year *t+1*. Moreover, we also show that there are limited differences in pre-trends, which provides some validation to our matching approach.

Figure 4 Panel B, uses the presence of AI job postings 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 a sharp increase in the probability of AI 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.

4.2 Main regressions

Table 3 presents the results for our main regression model outlined in Equation (1). Panel A presents the main results, where dependent variables are natural log of IT budget, indicator for posting an AI job posting, natural log of AI postings, and the raw count of AI job postings in columns (1)-(4), respectively. Column (4) is estimated using a PPML poisson regression, following suggestions from Cohn et al. (2022). Consistent with our hypothesis, we find a significant increase in digital investments across all four approaches, post PE investment, compared to the control group. Economically, PE investment is related to approximately 14.0%,

[8] For control firms, the event year is the year in which the treated firms receive PE transactions.

2.8%, 3.8%, higher IT budget, probability of posting at least one AI job, number of AI jobs, respectively. The poisson coefficient (1.178) in column (4) indicates that we observe 1.178 more AI postings post PE investment, compared to the pre period.

Panel B estimates the dynamic effects of the main regression results. Specifically, we interact relative years (e.g., two years, one year before the year of PE investment) on the *Treat* variable and re-estimate the main regression. 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. This alleviates the concern that PE investors invest in companies that already have digital investments in place.

Overall, the main regression results are consistent with our main hypothesis that PE investment is associated with increased digital investments of the portfolio companies. Particularly, the companies experience not only an increase in digital-related expenses, but also in the hiring of personnel of advanced digital technology skills, such as AI skills.

4.3 IT investments relative to Industry Benchmarks

One potential concern with our IT investment analysis, is that it is unclear if additional investment in IT relates to firms spending more to catch up with peers or over-spending compared to industry norms. The prior interpretation would suggest that IT investment is playing a positive role in digital transformation, while the latter would suggest that the additional IT investment could be counterproductive, or is being used inefficiently to maintain legacy computer or server systems. Thus, we examine whether our IT results are centered around the firms that had low IT spending before PE investment relative to industry peers, because these types of IT investments are more likely to be new investments in IT that have a positive impact on digital transformation.

To test this idea, we first measure whether a firm has made high or low IT investments before the PE investment. In particular, in Table 4 Panel A, we take the median IT investment scaled by firm sales in the industry (2-digit SIC code)-year, and divide our sample with firms with below median IT investment ("low IT investment firms") and above median IT investment ("high IT investment firms"), pre PE transaction. In Table 4 Panel B, we use the pooled sample and instead create an indicator that equals one if the firm had above-median IT-to-sales ratio pre PE investment, and zero otherwise. Our variable of interest is $Treat\ x\ Post\ x\ Above\ Median\ IT\ spending$, and we use the IT budget as the dependent variable.

The results in Table 4 suggest that the results are concentrated around firms with low IT investment pre PE investment. Panel A shows that the results hold only for firms with low IT investments pre-PE transaction (column (1)), where low IT investment firms experience a 28% increase in IT budget post PE transaction. Conversely, firms with high IT investments pre PE-transaction (column (2)) do not exhibit any significant increase. Similarly, Panel B shows a negative coefficient for the triple interaction variable, which suggests that we do not observe a meaningful increase in digital investments for firms that already have the investments in place. Overall, the analyses imply that PE investors are focused on 'transforming' the company rather than increasing maintenance costs for legacy IT infrastructure.

4.4 Alternative measures of digital investments

4.4.1 Within IT Budget

We first decompose the IT budgets from Aberdeen into subcategories to analyze whether we observe heterogeneous effects in different types of budgets. Table 5 uses the natural log of hardware budget, software budget, and communications budgets as dependent variables in columns (1), (2), and (3), respectively. We find similar magnitudes of increase across all measures post PE investment; 14.2%, 13.8%, and 13.5% increase in hardware, software, and communications budgets, respectively. The results are consistent with the notion that digital investments are spread across different dimensions.

4.4.2 Alternative measures

A concern with our analysis in Table 3 is that IT budgets and AI postings may not be the only measures which the PE investors exploit to enhance portfolio firms' digital technologies. To address this concern, we use alternative measures of digital technologies to study whether our main results are also robust to these measures. In particular, we use the number of acquired IT companies (Technology M&A), and the number of website analytics software at the portfolio company-level, as alternative measures of digital investments, and re-estimate our main analyses. For instance, portfolio firms may acquire IT companies to integrate their solutions into their portfolio firm strategies; alternatively, portfolio firms may subscribe to analytics software that could aid them analyze the corporate website visitors. The number of technology M&As is obtained from 451 data from S&P, and the number of website analytics is gathered from the website technology data in Builtwith.[9]

Table 6 reports the coefficients of the regressions. Panel A estimates OLS regressions which use the natural log of one plus Technology M&A (column (1)) and the natural log of one plus the number of website analytics software (column (2)) as dependent variables; Panel B

[9] Builtwith constructs this dataset by scraping websites for technological markers that are used to derive firms' investment in website technologies.

estimates PPML poisson regressions that use the number of Technology M&A and the number of website analytics software as dependent variables. Across all four specifications, the regressions show statistically significant coefficients and validate the idea that PE investors use various strategies to invest in digital technologies.

5. Cross-sectional regressions

5.1 Investor characteristics Technology investment expertise

Exploiting the investor-level variation, we test whether the results are stronger for deals where the PE investor has experience 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 other investments. The idea could also potentially explain the mechanisms behind our findings. We test this in three ways. First, we gauge the expertise in investing in the IT industry, by measuring whether the PE investor had at least one investment in an IT company previous to the transaction. In Table 7 we indeed find that is the case. Panel A regresses the same dependent variables described in the main regression (Equation (1)), on a triple interaction variable $Treat_i \times Post_{i,t} \times Prior\ Tech\ Deals_t$, in addition to $Treat_i \times Post_t$ which is used in the main regression. $Prior\ Tech\ Deals_t$ equals one if at least one of the investors has previously invested in a technology firm, and zero otherwise. Deals invested by PE investors that had previously invested in technology firms incrementally have 1.0%, 0.2%, and 0.6% higher IT budget, probability of an AI job posting, and the number of AI job postings, respectively.

Second, we show that the results are concentrated around PE investors that have personnel with digital-related experience in their firm. We do so by obtaining people data (which contains information on each person's latest position and their previous experience) from

Pitchbook and subsequently by classifying PE investors that have at least one person with digital-related experience (i.e., digital, data, or AI-related). The variable $Treat\ x\ Post\ x\ Digital\ Experience$ tests whether PE investors that have at least one person with digital experience increase portfolio firms' digital investments more than those without. Panel B documents results consistent with the notion, as the increase in IT budget, the probability of AI job posting (at the portfolio firm level), and the number of AI job postings are concentrated on investors with those characteristics.

Third, we test whether PE investors that hired an in-house AI expert are more likely to invest in digital technology. In Panel B, we test whether the results are concentrated around PE investors that have hired at least one AI personnel at their firm. Hiring an AI worker at the PE investor level could be a signal as to how important the investor believes digital technology to be a central part of the investor value-add strategy. The variable $Treat\ x\ Post\ x\ PE\ Digital\ Personnel$ is the variable of interest in this regression, where $PE\ AI\ Personnel$ equals one if the PE investor has hired at least one AI-related personnel and zero otherwise. Consistent with our predictions, in Panel B we find a significant increase for digital investments for portfolio firms invested by PE investors that have AI experts as employees.

Finally, we examine whether the board member's IT expertise could explain the results. The board member from the PE investor is the individual who influences and communicates with the portfolio firm management the most. Therefore, it is plausible that the board member's past experience can shape the portfolio firm's actions. Table 7 Panel C tests this idea, by regressing the dependent variables on $Treat\ x\ Post\ x\ PortCo\ Digital\ Board$, where $PortCo\ Digital\ Board$ 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 BoardEx data. We observe the results are significantly stronger for firms with PE board members having experience in sitting on IT company boards, across all dependent variables.

5.2 Transaction characteristics Non-IT/IT firms and buyout/growth equity transactions

In addition to investor characteristics, we study our main results across PE transaction characteristics. First, regarding portfolio firm characteristics, we assess whether our main findings are different between non-IT and IT portfolio firms. While we anticipate that the rate 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 previous literature documents the benefits of digital transformation in the non-IT industry as well (Babina et al., 2022; Chen and Srinivasan, 2023). To test this claim, we add the triple interaction variable $Treat_i \times Post_t \times IT_i$ to the main regressions, where IT_i equals one if the portfolio firm is in the IT industry, and zero otherwise.

Table 8 Panel A displays the results for the above test. For IT budgets, while we observe 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 would increase digital investments post PE deal. We also find the main effects are statistically significant when the natural log of AI postings are used as a dependent variable (column (3)). Therefore, we conclude that non-IT firms still show a positive increase in digital investments, post PE investment.

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 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. Contrary to buyout transactions, growth equity investors are more willing to focus on the portfolio firm's growth than maintaining profitability. Consistent with this argument, in Table IA2 we compare the deal characteristics between buyout and growth equity deals, growth equity portfolio firms exhibit much lower ROA (-0.42 and -0.28 for Aberdeen and BurningGlass sample, respectively) than buyout portfolio firms (0.05 and 0.08 for Aberdeen and BurningGlass sample, respectively). In this regard, we argue that portfolio firms that receive growth equity deals would show stronger growth in digital investments. Similar to the non-IT portfolio firm test, we add an indicator variable $Growth_i$ as a triple interaction, which equals one if the portfolio firm received a growth equity deal, and zero otherwise.

Table 8 Panel B presents the results on this test. Consistent with our predictions, we find that the increase in digital investments are stronger for growth equity transactions than for buyouts. Portfolio firms with growth equity investments are associated with 11.4%, 5.3%, and 11.2% stronger growth in IT budgets, probability of an AI job posting, and the number of AI job postings than portfolio firms that underwent a buyout transaction. Collectively, the results are consistent with the idea that portfolio companies from growth equity deals, tend to exhibit stronger increases in digital investment after PE entry.

6 Consequences of digital investments

6.1 Sales and employee growth

Our results so far have suggested that PE investments are associated with different measures of digital investments. A natural question that may arise is the consequences of the digital transformation to the portfolio firms; we therefore test whether digital investments are associated with beneficial consequences. Specifically, in Table 9, we test whether the investments that experienced greater increases in digital transformation are associated with greater sales and employee growth for all companies (Panel A) and for non-IT firms (Panel B). We specifically test non-IT portfolio companies to reduce the concern that the results may be driven by IT companies. Specifically, we regress sales (and employee) 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 indicator for whether there was an increase in the digital investments (AI 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 sales growth. Specifically, portfolio firms that show an increase in AI job postings (columns (1) and (2)) and IT budget (columns (3) and (4)) are associated with 6.6% (column (1)) and 9.4% (column (3)) stronger sales growth, and 7.5% (column (2)) and 11.2% (column (4)) stronger employee growth respectively. Panel B exhibits a similar pattern when we restrict our sample to non-IT firms.

6.2 Innovation

In addition to their impact on sales and employee growth, digital technologies can also enhance innovation efficiency to those who adopt them. For instance, Babina et al., (2022) show that adoption of digital technologies is associated with enhanced productivity and development of new products and services; similarly, Cockburn et al., (2018) document that implementing digital technologies is associated with improving innovation processes. PE investors may also be interested in investing in digital technologies precisely for this reason; supporting this conjecture, Lerner et al., (2011) show that PE portfolio firms strengthen their innovation quality once PE investors invest in the firm. We test these claims by taking a similar approach to Table 9; specifically we measure and regress the changes (from one year before PE investment to two years after the PE investment and annualized) in indicators for or the number of patents filed in the calendar year compared to matched controls, on the indicator variable that equals one if the portfolio firm increased either AI job postings or IT budgets during one year before and after the PE investment relative to matched controls, and zero otherwise.

Table 10 reports the regression results. Panel A (Panel B) shows the results for the full sample (Non-IT sample). For both panels, columns (1) and (2) report results using the indicator for increases in AI job postings as the independent variable; columns (3) and (4) report results using the indicator for positive changes in IT budgets. We demonstrate that an increase in AI job postings is related to an increase in both patent indicators and the number of patents. The results are consistent when we restrict our sample to non-IT firms. Conversely, we do not find significant changes in patents for portfolio firms that underwent an increase in IT budgets. Our explanation for this result is that AI technologies have specific features that could substantially improve the innovation process, as suggested by recent work on the potential of these technologies (Cockburn et al., 2018). Specifically, whereas AI personnel are much more likely to be used for enhancing innovation productivity, IT budgets can be used for non-innovation purposes, such as cutting costs or streamlining HR procedures.

7. Conclusion

In this study, we analyze and find a substantial increase in portfolio firm's digital transformation post PE transaction. Specifically, we find an increase in IT budgets, number of AI-related job postings of the portfolio firm post PE investment. The increase is mainly driven by investors who have exposure to IT investments, and by growth equity deals. Non-IT investments also experience a sizable growth in IT investments. We also find the investments to benefit the portfolio firms, as we document that PE portfolio companies with an increase in digital investments, tend to also increase in sales and employee growth and also innovation activity, as measured by patenting activity.

We contribute to academic literature in three ways. First, 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, make digital transformations to their portfolio firms to accelerate their growth. Second, we show that the determinants of PE investing are shifting towards firms that are transformable using digital technology. Third, we contribute to the digital transformation literature by demonstrating how sophisticated investors, in a private firm setting, can contribute to firms' digital transformation.

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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*.
IT Budget-to-sales	Total annual IT budgets reported in *Aberdeen* scaled by total sales reported in *Dun and Bradstreet*.
AI Job Postings	Total number of job postings with AI skills from *BurningGlass* in the calendar year. List of AI skills follows Alekseeva et al (2021). Observations of above the 99% percentile of total job postings are dropped.
AI Job Postings-to-Employees	Total number of AI job postings scaled by total number of employees reported in *Dun and Bradstreet*.
Website Analytics Software	Total number of analytics software on the firm's website in the calendar year, data taken from *Builtwith*.
Technology M&As	Total number of technology M&As in the calendar year, data taken from *S&P 451* database.
Digital Expertise in the PE Fund:	
Prior Tech Deals	Total number of prior IT deals for the PE fund.
Presence of Personnel with Digital Experience	Indicator coded as one if the fund has more than one person that has digital experience, as indicated in the biography recorded in PitchBook.
Presence of AI Personnel	Indicator coded as one if the fund posts more than one AI job posting in the calendar year and zero otherwise.
Digital Board Member	Total number of PE-fund board members that also serve on boards of IT companies in the calendar year.
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 (2023).
Operating Variables:	
Log(Sales)	Logarithm of total annual sales, where sales is measured using *Dun and Bradstreet*.
Sales growth	Relative change in 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*.
Employee growth	Relative change in annual employees, where employees 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*.

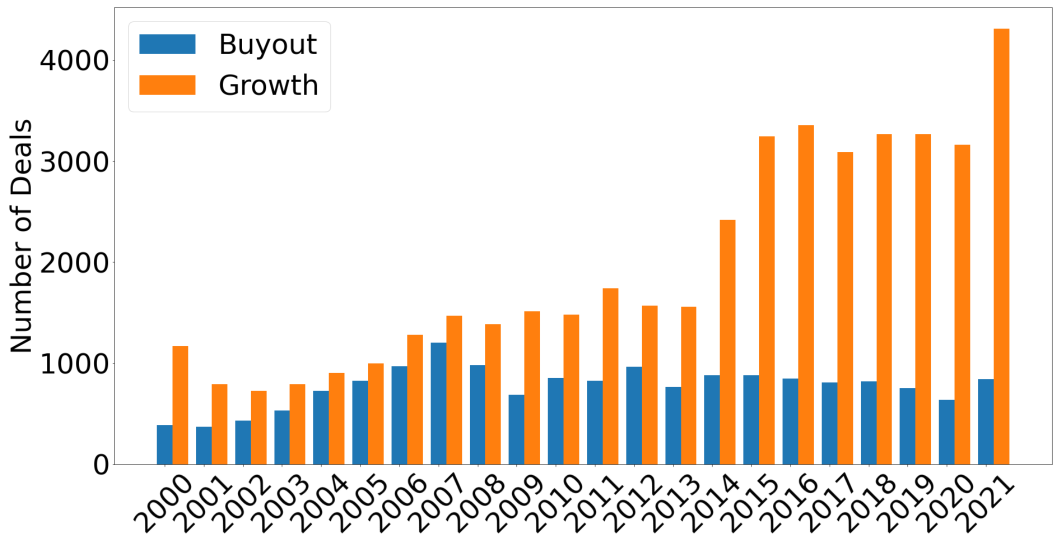
Innovation Variables:

Patents	Total number of patents filed in the calendar year, data taken from *USPTO*.
Patents Indicator	Indicator coded as one if the total number of patents filed in the year is greater than zero and zero otherwise.

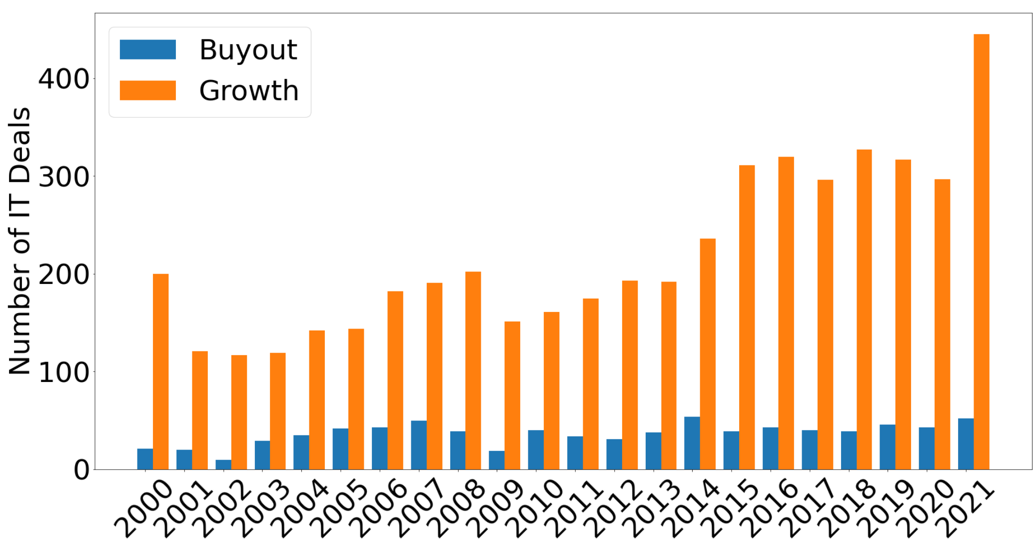
Pre-Deal Operating Variables:

Log(Sales)	Logarithm of total annual revenues, where revenues is measured using *CapitalIQ* pre-deal data.
ROA	Ratio of annual earnings before interest, taxes, depreciation and amortization (EBITDA) to total assets, where EBITDA and assets are measured using *CapitalIQ* pre-deal data.
LOSS	Indicator variable coded as one if annual earmings before interest, taxes, depreciation and amortization (EBITDA) is greater than zero, else otherwise. EBITDA are measured using *CapitalIQ* pre-deal data.
Turnover	Ratio of total annual revenues to total assets, where revenues and assets are measured using *CapitalIQ* pre-deal data.
Margins	Ratio of annual earnings before interest, taxes, depreciation and amortization (EBITDA) to total revenues, where EBITDA and revenues are measured using *CapitalIQ* pre-deal data.
Leverage	Ratio of total annual debt to total assets, where debt and assets are measured as of the deal announcement using *CapitalIQ* data.

Tables and Figures

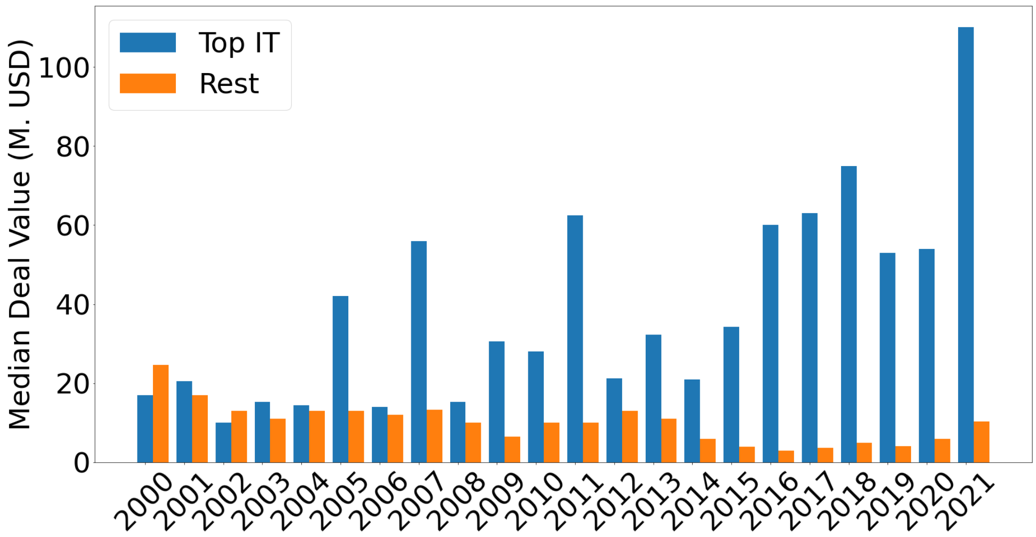


(a) All Deals

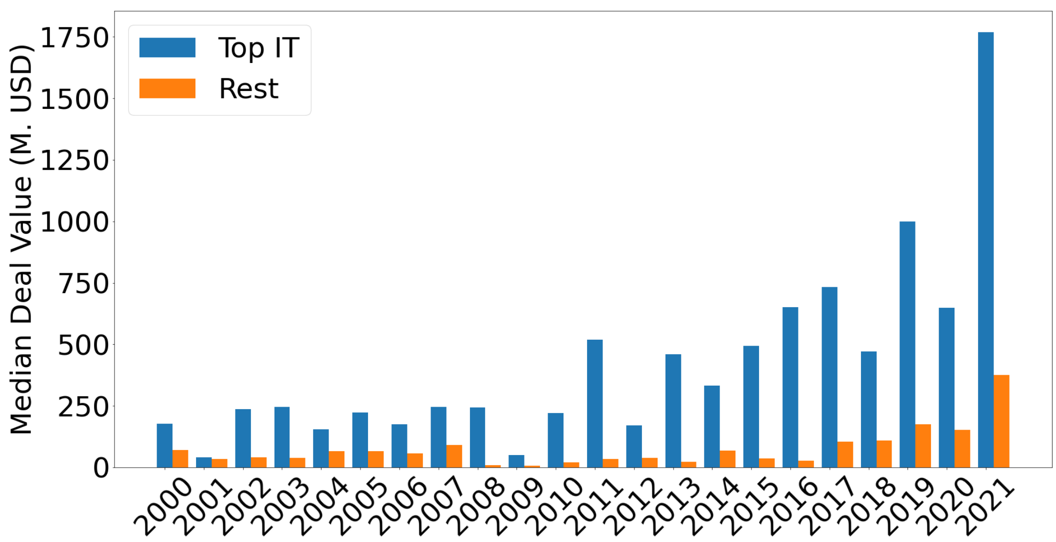


(b) IT-related Deals

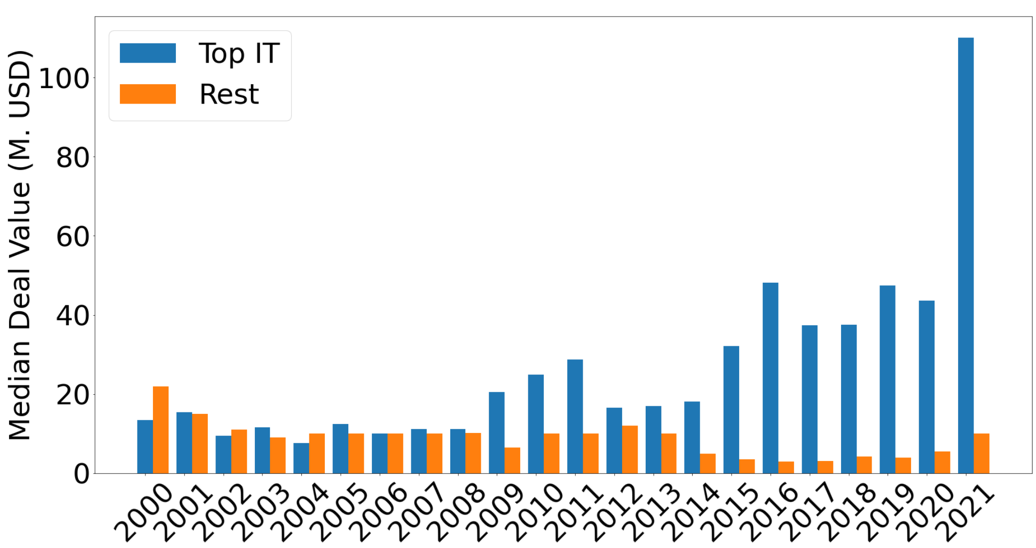
Figure 1: Time-series Distribution of (a) Total Buyout and Growth Equity Deals and (b) IT-related Buyout and Growth Equity Deals



(a) High IT Investor/Rest Deals



(b) High IT Investor/Rest Buyout Deals



(c) High IT Investor/Rest Growth Equity Deals

Figure 2: Time-series Median of Deal Values Across Deals from the Top-100 IT Spending PE Investors and the Rest in (a) All and (b) Buyout and (c) Growth Equity Deals. We Rank the PE investors by the Change in IT spending over the (+1,-1) Horizon Around the PE Entry year, for All PE investors with More than 5 Portcos that are Covered by Aberdeen.

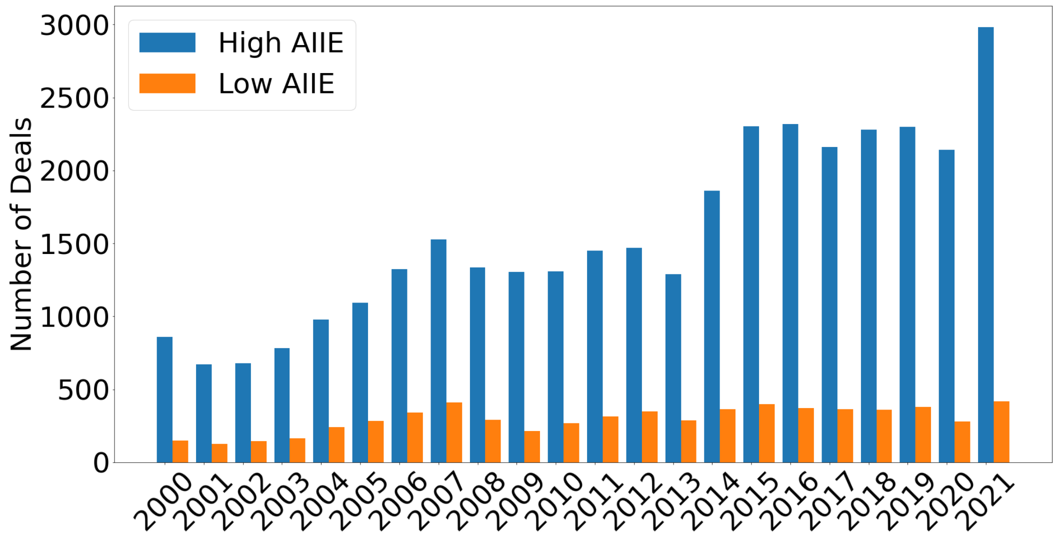
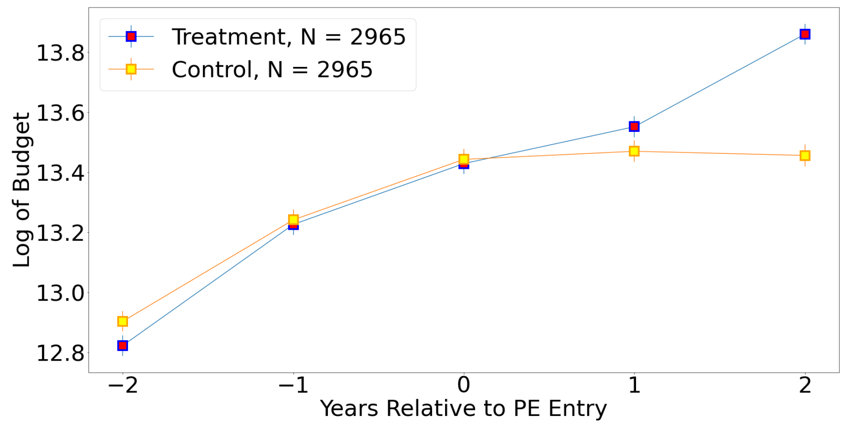
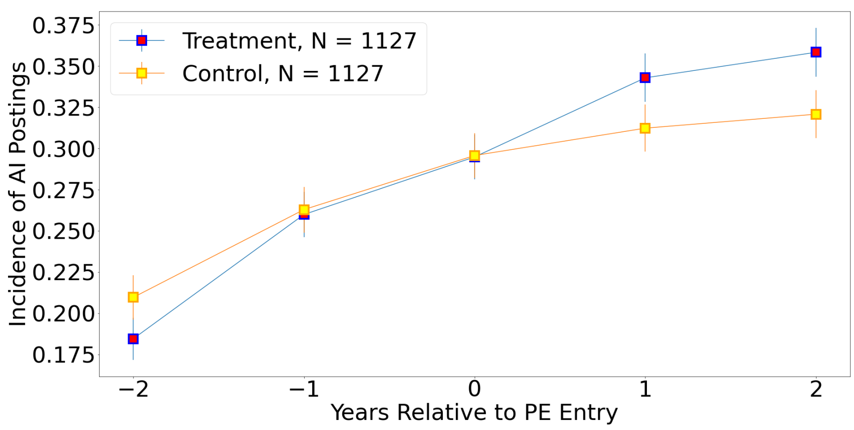


Figure 3: Time-series Distribution of Total Deals in Industries with High or Low AI Industry Exposure (AIIE)



(a) IT Budget



(b) Probability of AI Job Posting

Figure 4: Logarithm of IT budget (Panel A) or Probability of AI Job Posting (Panel B) around PE Investment Year for the Matched Sample of Portfolio Companies with 5-Year Consistent Time-Series. Error Bars Denote the 99% Confidence Interval.

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 *Aberdeen* and *BurningGlass* sample. We present the statistics of five variables, namely, the number of employees, sales in millions, sales growth, IT budget in millions and the number of AI job postings. We present the summary statistics across two samples — (1) the *Aberdeen* sample which is used to measure IT-budgets (in Panel B). (2) the *BurningGlass* sample (in Panel C) which is used to measure AI job postings.

Panel A: Deal Breakdowns

	Deal Type		PortCo Type	
	Growth Equity	Buyout	Non-IT	IT
Aberdeen Sample	5940	1541	5041	2440
BurningGlass Sample	3613	1034	2921	1726

Panel B: Aberdeen Sample

	Mean	SD	Median	25%	75%	N
No. of Employees	219.33	295.08	85	30	251	55532
Total Sales (Millions)	36.77	45.07	15.23	4.6	49.8	55532
Sales Growth	0.1	0.48	0	-0.01	0.1	55532
IT Budget (Millinos)	13.23	1.93	13.13	11.85	14.41	55532

Panel C: BurningGlass Sample

	Mean	SD	Median	25%	75%	N
No. of Employees	138.92	105.81	106	39	276	27290
Total Sales (Millions)	19.11	12.9	20	5.87	32.8	27290
Sales Growth	0.17	0.57	0	-0.01	0.15	27290
No. of AI Job Postings	2.36	13.21	0	0	0	27290
Indicator of AI Job Posting	0.22	0.42	0	0	0	27290

Table 2: AlexNet and PE Target Characteristics

This table examines the changing PE target characterstics across time, using the introduction of a breakthrough AI technology, AlexNet, as a reference point. In Panel A, we regress an indicator for the time period after the introduction of AlexNet in 2012 or the number of years relative to 2012, on an indicator for whether the portfolio firm is in an industry that exhibits high AI potential (Felten et al, 2021) and other PE target characteristics that are measured before the deal. In Panel B, we regress an indicator for whether the firm exhibits high IT budgets or AI job postings changes around the PE entry, on the indicator for whether the portfolio firm is in an industry that exhibits high AI potential (Felten et al, 2021) and year fixed effects. Standard errors clustered at the industry and year-level are reported. ***, **, * denote significance at the 1%, 5% and 10% level.

Panel A: Characteristics of PE Targets After AlexNet

	(1)	(2)	(3)	(4)
	Post(AlexNet)	Post(AlexNet)	Years Relative to AlexNet	Years Relative to AlexNet
High AI Potential$_i$	0.076***	0.097**	0.933***	1.081**
	(0.026)	(0.038)	(0.323)	(0.468)
Size$_i$		0.002		0.063
		(0.005)		(0.066)
Turnover$_i$		-0.024**		-0.243*
		(0.011)		(0.134)
Profit Margin$_i$		-0.000		-0.001*
		(0.000)		(0.000)
Loss Indicator$_i$		0.115***		1.093**
		(0.036)		(0.475)
Leverage$_i$		0.003		0.072*
		(0.003)		(0.041)
Observations	40,946	2,906	40,946	2,906
R^2	0.0032	0.0266	0.0032	0.0189

Panel B: AI Potential and Digitalizing PE Targets

	(1)	(2)
	High IT Budget Change	High AI Job Postings Change
High AI Potential$_i$	0.266***	0.106**
	(0.033)	(0.047)
Year FE	Yes	Yes
Observations	7,268	3,487
R^2	0.1409	0.0410

Table 3: PE Entry and Digital Investment

This table reports the regression analysis of IT budgets and AI job postings on the PE entry event. In Panel A, we examine the logarithm of IT budgets, indicator for AI job postings, logarithm of 1 + number of AI job postings, the total number of AI job postings (in a Poisson regression, with estimates reported in average margins). In Panel B, study the pre- and post-trends of IT budgets, indicator for AI job postings and the logarithm of 1 + number of AI job postings around the PE entry event. 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 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)
	Log(IT Budget)	AI Postings (Indicator)	AI Postings (Logarithm)	AI Postings (Poisson Count)
$\text{Treat}_i \times \text{Post}_{i,t}$	0.140**	0.028**	0.038***	1.178**
	(0.056)	(0.010)	(0.010)	(0.529)
Firm FE	Yes	Yes	Yes	Yes
Matched Pair-Year FE	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes
Observations	55,532	27,290	27,290	4,504
R^2	0.6215	0.6215	0.6215	0.7938

Panel B: Main Analysis - Pre and Post

	(1)	(2)	(3)
	Log(IT Budget)	AI Postings (Indicator)	AI Postings (Logarithm)
$\text{Treat}_i \times \text{Pre}_{i,t=-2}$	-0.048	-0.013	-0.023
	(0.052)	(0.011)	(0.016)
$\text{Treat}_i \times \text{Pre}_{i,t=-1}$	-0.036	-0.015	-0.011
	(0.036)	(0.013)	(0.011)
$\text{Treat}_i \times \text{Post}_{i,t=1}$	0.159**	0.031***	0.046***
	(0.055)	(0.009)	(0.011)
$\text{Treat}_i \times \text{Post}_{i,t=2}$	0.277***	0.030**	0.057***
	(0.056)	(0.010)	(0.015)
Firm FE	Yes	Yes	Yes
Matched Pair-Year FE	Yes	Yes	Yes
Controls	Yes	Yes	Yes
Observations	55,532	27,290	27,290
R^2	0.9698	0.8585	0.9102

Table 4: 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 the logarithm of 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 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)
Sample	Low IT-to-Sales before PE Investment	High IT-to-Sales before PE Investment
Dependent Variable	Log(IT Budget)	Log(IT Budget)
$\text{Treat}_i \times \text{Post}_{i,t}$	0.251***	-0.030
	(0.072)	(0.058)
Firm FE	Yes	Yes
Year FE	No	No
Matched Pair-Year FE	Yes	Yes
Controls	Yes	Yes
Observations	34,193	21,339
R^2	0.9634	0.9775

Panel B: Interaction Analysis

	Log(IT Budget)
$\text{Treat}_i \times \text{Post}_{i,t}$	0.243***
	(0.069)
$\text{Treat}_i \times \text{Post}_{i,t} \times$Above Median IT-to-Sales Before PE Invest	-0.262***
	(0.069)
Firm FE	Yes
Year FE	No
Matched Pair-Year FE	Yes
Controls	Yes
Observations	55,532
R^2	0.9698

Table 5: 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. As dependent variable, we examine the logarithm of hardware IT budgets, software IT budget, and communication 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). Control variables include the log of sales, employees 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)
	Log(Hardware Budget)	Log(Software Budget)	Log(Comm. Budget)
$\text{Treat}_i \times \text{Post}_{i,t}$	0.142**	0.138**	0.135**
	(0.056)	(0.057)	(0.060)
Firm FE	Yes	Yes	Yes
Matched Pair-Year FE	Yes	Yes	Yes
Controls	Yes	Yes	Yes
Observations	55,532	55,532	55,532
R^2	0.9682	0.9686	0.9562

Table 6: PE Entry and Other Forms of Digital Investment

This table reports the regression analysis of technology M&A and website analytics software on the PE entry event. In Panel A, we examine the logarithm of the number of technology M&A +1 and the logarithm of the number of website analytics software around the PE entry event. In Panel B, we examine the poisson regression on the number of technology M&A +1 and the number of website analytics software around the PE entry event (estimates are reported in average margins). 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 and sales growth. Standard errors are clustered at the firm and year-level. ***, **, * denote significance at the 1%, 5% and 10% level.

Panel A: Logarithm of Count		
	(1)	(2)
	Log(Technology M&A + 1)	Log(Website Analytics Software + 1)
$\text{Treat}_i \times \text{Post}_{i,t}$	0.027***	0.084***
	(0.005)	(0.012)
Firm FE	Yes	Yes
Matched Pair-Year FE	Yes	Yes
Controls	Yes	Yes
Observations	55,566	51,020
R^2	0.8368	0.9834
Panel B: Poisson Regression of Count		
	(1)	(2)
	Number of Technology M&A	Number of Website Analytics Software
$\text{Treat}_i \times \text{Post}_{i,t}$	0.416*	0.421***
	(0.252)	(0.053)
Firm FE	Yes	Yes
Matched Pair-Year FE	Yes	Yes
Controls	Yes	Yes
Observations	732	40,116
R^2	0.1678	0.6215

Table 7: PE Investment, PE Expertise and Digital Transformation

This table reports the regression analysis of IT budgets and AI job postings on the PE entry event and the digital technology expertise at the PE investor level. In Panel A, we examine the logarithm of IT budgets, indicator for AI job postings, and logarithm of 1+ number of AI job postings for PE deals that are backed by PE investors with prior tech deals. In Panel B, we perform the same analysis for PE deals where the PE fund has personnel with digital expertise, as measured by the biographies in Pitchbook. In Panel C, we perform the same analysis for PE deals that are backed by PE investors with AI personnel. In Panel D, we perform the same 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). 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 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 No. of Prior Tech Deals

	(1)	(2)	(3)
	Log(IT Budget)	AI Postings (Indicator)	AI Postings (Logarithm)
$\text{Treat}_i \times \text{Post}_{i,t}$	0.116**	0.021*	0.017
	(0.051)	(0.011)	(0.011)
$\text{Treat}_i \times \text{Post}_{i,t} \times \text{Prior Tech Deals}_d$	0.010***	0.002**	0.006**
	(0.003)	(0.001)	(0.002)
Firm FE	Yes	Yes	Yes
Matched Pair-Year FE	Yes	Yes	Yes
Controls	Yes	Yes	Yes
Observations	55,532	27,290	27,290
R^2	0.9693	0.8584	0.9102

Panel B: Digital Expertise Measured by the Presence of Personnel with Digital Experience

	(1)	(2)	(3)
	Log(IT Budget)	AI Postings (Indicator)	AI Postings (Logarithm)
$\text{Treat}_i \times \text{Post}_{i,t}$	0.110**	0.016	0.017
	(0.049)	(0.013)	(0.015)
$\text{Treat}_i \times \text{Post}_{i,t} \times \text{Digital Experience}_d$	0.090***	0.028*	0.049**
	(0.027)	(0.013)	(0.022)
Firm FE	Yes	Yes	Yes
Matched Pair-Year FE	Yes	Yes	Yes
Controls	Yes	Yes	Yes
Observations	55,532	27,290	27,290
R^2	0.9693	0.8584	0.9101

Panel C: Digital Expertise Measured by the Presence of AI Personnel

	(1)	(2)	(3)
	Log(IT Budget)	AI Postings (Indicator)	AI Postings (Logarithm)
$\text{Treat}_i \times \text{Post}_{i,t}$	0.127**	0.024*	0.031**
	(0.052)	(0.012)	(0.012)
$\text{Treat}_i \times \text{Post}_{i,t} \times \text{PE Digital Personnel}_d$	0.258***	0.055*	0.107*
	(0.077)	(0.029)	(0.051)
Firm FE	Yes	Yes	Yes
Matched Pair-Year FE	Yes	Yes	Yes
Controls	Yes	Yes	Yes
Observations	55,532	27,290	27,290
R^2	0.9693	0.8584	0.9101

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

	(1)	(2)	(3)
	Log(IT Budget)	AI Postings (Indicator)	AI Postings (Logarithm)
$\text{Treat}_i \times \text{Post}_{i,t}$	0.071*	0.000	-0.017
	(0.036)	(0.010)	(0.013)
$\text{Treat}_i \times \text{Post}_{i,t} \times \text{PortCo Digital Board}_d$	0.162*	0.051***	0.102***
	(0.078)	(0.016)	(0.026)
Firm FE	Yes	Yes	Yes
Matched Pair-Year FE	Yes	Yes	Yes
Controls	Yes	Yes	Yes
Observations	55,532	27,290	27,290
R^2	0.9693	0.8585	0.9102

Table 8: Cross-Sectional Analysis: Non-IT/IT Firms and Buyout/Growth Equity Deals

This table reports the regression analysis of IT budgets and AI job postings on the PE entry event and the nature of the PE deal. In Panel A, we examine the logarithm of IT budgets, indicator for AI job postings, and logarithm of 1+ number of AI job postings for portfolio companies that are either IT or non-IT. In Panel A, we examine the logarithm of IT budgets, indicator for AI job postings, and logarithm of 1+ number of AI job postings 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 and sales growth. Standard errors are clustered at the firm and year-level. ***, **, * denote significance at the 1%, 5% and 10% level.

Panel A: Non-IT and IT Firms

	(1)	(2)	(3)
	Log(IT Budget)	AI Postings (Indicator)	AI Postings (Logarithm)
$\text{Treat}_i \times \text{Post}_{i,t}$	0.106**	0.016	0.032**
	(0.045)	(0.012)	(0.011)
$\text{Treat}_i \times \text{Post}_{i,t} \times \text{IT}_d$	0.107*	0.028*	0.015
	(0.050)	(0.015)	(0.026)
Firm FE	Yes	Yes	Yes
Year FE	No	No	No
Matched Pair-Year FE	Yes	Yes	Yes
Controls	Yes	Yes	Yes
Observations	55,532	27,290	27,290
R^2	0.9693	0.8584	0.9101

Panel B: Growth Equity and Buyout Deals

	(1)	(2)	(3)
	Log(IT Budget)	AI Postings (Indicator)	AI Postings (Logarithm)
$\text{Treat}_i \times \text{Post}_{i,t}$	0.051	-0.013	-0.048*
	(0.047)	(0.017)	(0.023)
$\text{Treat}_i \times \text{Post}_{i,t} \times \text{Growth}_d$	0.114*	0.053***	0.112***
	(0.061)	(0.017)	(0.029)
Firm FE	Yes	Yes	Yes
Year FE	No	No	No
Matched Pair-Year FE	Yes	Yes	Yes
Controls	Yes	Yes	Yes
Observations	55,532	27,290	27,290
R^2	0.9693	0.8585	0.9102

Table 9: 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 use an indicator that is coded 1 if the firm exhibits > 0 difference in the s+1 and s-1 levels of either AI job postings or IT budgets around the PE entry year s relative to matched control firm changes, and 0 otherwise. Controls are also defined in changes and include sales-to-employees and log of employees for the sales growth regressions. We include log of sales and sales-to-employees as controls for the employee growth regressions. Panel A performs the analysis on the full sample of PE portfolio companies, while Panel B performs the analysis for the sub-sample of PE portfolio companies from non-IT industries. 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. Standard errors are clustered at the treatment cohort level. ***, **, * denote significance at the 1%, 5% and 10% level.

Panel A: Full Sample

Investment Variable	AI Job Postings		IT Budgets	
Dependent Variable	Δ Sales Growth$_{s+2,s-1}$	Δ Employee Growth$_{s+2,s-1}$	Δ Sales Growth$_{s+2,s-1}$	Δ Employee Growth$_{s+2,s-1}$
	(1)	(2)	(3)	(4)
Increase Investment$_{s+1,s-1}$	0.066***	0.075**	0.094***	0.112***
	(0.020)	(0.026)	(0.027)	(0.018)
Treatment Cohort FE	Yes	Yes	Yes	Yes
Observations	1,307	1,307	4,232	4,238
R^2	0.5542	0.3770	0.3378	0.1408

Panel B: Non-IT Firms

Investment Variable	AI Job Postings		IT Budgets	
Dependent Variable	Δ Sales Growth$_{s+2,s-1}$	Δ Employee Growth$_{s+2,s-1}$	Δ Sales Growth$_{s+2,s-1}$	Δ Employee Growth$_{s+2,s-1}$
	(1)	(2)	(3	(4)
Increase Investment$_{s+1,s-1}$	0.059*	0.107***	0.064**	0.087***
	(0.026)	(0.029)	(0.024)	(0.017)
Treatment Cohort FE	Yes	Yes	Yes	Yes
Observations	791	791	2,974	2,980
R^2	0.5299	0.3334	0.3107	0.0899

Table 10: Post PE Entry Changes in Digital Investment and Innovation

This table reports the regression of patents on PE portfolio companies and invest in digital technologies around the PE entry event. To measure changes in innovation activity, we measure the difference in s+2 and s-1 levels of an indicator for patents filed or the number of patents filed around the PE entry year s, relative to the difference in the patent variables over the same horizon in matched control firms. To measure changes in digital investment, we use an indicator that is coded 1 if the firm exhibits > 0 difference in the s+1 and s-1 levels of either AI job postings or IT budgets around the PE entry year s relative to matched control firm changes, and 0 otherwise. Controls are also defined in changes and include log of sales, log of employees and sales-to-employees as controls. Panel A performs the analysis on the full sample of PE portfolio companies, while Panel B performs the analysis for the sub-sample of PE portfolio companies from non-IT industries. 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. Standard errors are clustered at the treatment cohort level. ***, **, * denote significance at the 1%, 5% and 10% level.

Panel A: Full Sample				
Investment Variable	AI Job Postings		IT Budgets	
Dependent Variable	Patent Indicator$_{s+2,s-1}$	Patent$_{s+2,s-1}$	Patent Indicator$_{s+2,s-1}$	Patent$_{s+2,s-1}$
	(1)	(2)	(3)	(4)
Increase Investment$_{s+1,s-1}$	0.080***	0.253***	0.009	0.006
	(0.011)	(0.066)	(0.013)	(0.021)
Treatment Cohort FE	Yes	Yes	Yes	Yes
Observations	1,307	1,307	4,238	4,238
R^2	0.0135	0.0166	0.0025	0.0029

Panel B: Non-IT Firms				
Investment Variable	AI Job Postings		IT Budgets	
Dependent Variable	Patent Indicator$_{s+2,s-1}$	Patent$_{s+2,s-1}$	Patent Indicator$_{s+2,s-1}$	Patent$_{s+2,s-1}$
Increase Investment$_{s+1,s-1}$	0.074***	0.219*	0.011	0.006
	(0.020)	(0.107)	(0.018)	(0.031)
Treatment Cohort FE	Yes	Yes	Yes	Yes
Observations	791	791	2,980	2,980
R^2	0.0136	0.0231	0.0023	0.0025

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	4.38	1.47	4.39	7467	4.34	1.56	4.33	7467	0.03
Log Sales	16.35	1.7	16.5	7467	16.3	1.66	16.38	7467	0.05*
Panel B: BurningGlass Sample									
	Treated				Control				Differences
	Mean	SD	Median	N	Mean	SD	Median	N	Mean
Log Employees	4.29	1.23	4.51	4623	4.27	1.31	4.57	4623	0.02
Log Sales	16.09	1.39	16.54	4623	16.1	1.44	16.61	4623	-0.01

Table IA.2: Deal Characteristics Across Growth Equity and Buyout Deals

This table presents the difference in deal characteristics across growth equity and buyout deals. We examine several deal characteristics namely, logarithm of sales, return-on-assets (ROA), asset turnover (Turnover), profit margins (Margins), an indicator for loss firms and an indicator for an IT firm. Columns 1-4 presents the sample statistic of the portcos from growth equity deals and columns 5-8 presents the same for portcos from buyout deals. Differences in the mean are reported in column 9 with the independent 2-sample t-test statistic. Panel A reports the comparison in the Aberdeen sample, and Panel B reports the comparison in the BurningGlass sample. ***, **, * denote significance at the 1%, 5% and 10% level.

Panel A: Aberdeen Sample

	Growth Equity				Buyout				Differences
	Mean	SD	Median	N	Mean	SD	Median	N	Mean
Log(Sales)	4.03	2.57	3.91	576	5.56	1.4	5.56	196	-1.52***
ROA	-0.42	0.73	-0.12	468	0.05	0.16	0.09	126	-0.48***
Turnover	0.65	0.69	0.39	557	0.98	0.64	0.81	131	-0.33***
Margins	-2.39	4.66	-0.13	468	0.11	0.2	0.12	133	-2.50***
Loss Firm	0.59	0.49	1	468	0.15	0.36	0	133	0.44***
IT Firm	0.2	0.4	0	576	0.36	0.48	0	196	-0.16***

Panel B: BurningGlass Sample

	Growth Equity				Buyout				Differences
	Mean	SD	Median	N	Mean	SD	Median	N	Mean
Log(Sales)	4.64	2.08	4.56	297	5.67	1.22	5.74	160	-1.03***
ROA	-0.28	0.51	-0.1	261	0.08	0.1	0.1	100	-0.36***
Turnover	0.76	0.73	0.52	280	1.05	0.65	0.86	102	-0.29***
Margins	-1.32	2.8	-0.09	261	0.12	0.14	0.11	107	-1.44***
Loss Firm	0.57	0.5	1	261	0.11	0.32	0	107	0.46***
IT Firm	0.25	0.43	0	297	0.36	0.48	0	160	-0.12**