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Capital Adjustment, Technology Vintages and Training: Role of capital investment spikes in firm's skill formation strategy

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Capital Adjustment, Technology Vintages and Training *

Role of capital investment spikes in firm's skill formation strategy

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Abstract

We study how investment spikes in technologies and complementary infrastructure influence firms' hiring and training strategies. While prior work emphasizes how technologies reallocate skill demand, few focus on how firms acquire the required skills. Using linked employer-employee data on German establishments, we identify spikes by their technological composition and capital vintages. Event study estimates show that investment spikes in ICT and production line technologies lead to an *upscaling* effect raising employment by external hiring followed by training of young apprentices. Combining technologies with factories and plants induces firms to use apprenticeship training without an increase in external hiring. Incumbent workers are trained when investment spikes renew the vintage of firm's capital. Our findings support a vintage human capital framework in which technology adoption induces firms to gradually adjust workforce through hiring and training while preserving expertise of incumbent workers.

Keywords: Investment spikes, Technology adoption, Technology vintages, Training, Skill formation.

JEL Codes: J24, D22, O33

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1 Introduction

Firms adopting new capital often face a misalignment between the skills of its existing workers and the technologies embodied in the new capital. While existing literature documents how technology adoption shifts the demand for skills towards high skilled and non-routine tasks[1], much less is known about the personnel strategies firms use to meet this demand. The technology induced demand for labor requires firms to develop skills by training incumbent workers, expanding apprenticeships or hiring new workers with required skills (Wolter and Ryan, 2011; Hoffman and Stanton, 2024). These skill formation strategies can be combined in a portfolio since such decisions depend not only on relative costs of hiring and training but also on the composition and vintage of technologies (Acemoglu and Restrepo, 2019)[2]. These strategic choices shape how workers enter the labor market, how older cohorts become obsolete, and how skill formation practices respond to technological change.

While studies have investigated the employment and training effects of technology adoption, much of this work overlooks how firms combine such strategies. On one hand, seminal studies focusing on employment effects highlight the reallocation potential of technologies whilst being silent on how firms adapt their training investments[3]. On the other hand, studies on training miss the employment effects of new technologies[4]. Since introduction of new technology vintages does not make existing capital and labor obsolete, firms do not have an incentive to completely overhaul their workforce structure by firing existing workers (Asphjell et al., 2014). Moreover, firms have an incentive to invest in training of incumbent workers and apprentices to optimize the human capital for specific capital vintages even when such training is done in transferable skills (Chari and Hopenhayn, 1991; Acemoglu and Pischke, 1999a,b).

We identify capital adjustment through large, irregular and irreversible bursts of capital expenditure referred as "investment spikes" (Doms and Dunne, 1998; Fishman and Jovanovic, 2021). At the macro level, investment spikes positively influence aggregate investment (Gou-

[1]See Mondolo (2022) and Hötte et al. (2023) for a systematic review of the empirical literature. These studies point towards 1) lack of labor displacement effect of technologies (such as ICT, Robots and other measures), and 2) a reallocation of labor across workers, occupations, firms and sectors. See Brynjolfsson et al. (2025) for a recent review on the relation between artificial intelligence technologies and employment.

[2]Due to supply-side constraints, hiring frictions in search and adaptation costs for new workers, rational firms would use a combination of these skill formation strategies to achieve the optimal level of human capital (Hamermesh and Pfann, 1996; Dionisius et al., 2009; Aepli et al., 2024)

[3]See Aghion et al. (2020); Domini et al. (2021); Bessen et al. (2023) for automation technologies, Dauth et al. (2021); Koch et al. (2021) for industrial robots and Acemoglu et al. (2022); Rammer et al. (2022); Babina et al. (2024) for the effects of artificial intelligence on labor market outcomes at the firm level.

[4]See Boothby et al. (2010); Brunello et al. (2023); Müller (2024)

rio and Kashyap, 2007; Disney et al., 2020). At the micro level, investment spikes are followed by an increase in labor demand with ambiguous effects on productivity (Nilsen et al., 2008). While a positive productivity effect reflects revenue growth exceeding employment growth (due to product demand and scale economies), a negative effect points to learning frictions and the need for additional training and workforce adjustment (Grazzi et al., 2016). However, the investment spike literature does not incorporate the role of personnel strategies in how firms learn from new technologies. Furthermore, due to data limitations, studies do not explore the technological and vintage composition of investment spikes[5].

In this paper, we fill these gaps by studying how and to what extent the technological content of capital adjustment influences firm's skill formation strategies. First, we define skill formation strategies by employment growth (overall and specifically for young workers), apprenticeship training and further training of incumbent workers. Second, we use twenty years of a linked employer-employee data for a representative sample of establishments in Germany[6] (Ruf et al., 2021). This allows us to observe long-term investment behavior at the plant level, identify investment spike episodes and link survey with administrative data on workers and establishments. The German context fits our study as firms actively pursue strategies to optimize their skills mix (Pfeifer and Backes-Gellner, 2018), pursue growth oriented technological investments (Dauth et al., 2021) and lack of prior literature on investment spikes. Third, we exploit the timing of investment spike events using a stacked DiD event study design to derive causal effects of investment spikes on skill formation strategies (Cengiz et al., 2019; Bessen et al., 2023; Wing et al., 2024). Fourth, we decompose investment spikes by the technological composition (ICT, production facilities and other purchases) and the vintage renewal of the capital stock (old versus new vintage of capital). To the best of our knowledge, our work is the first to provide a technological decomposition of investment spikes and link it with firm-level skill formation strategies.

We find that investment spikes lead to structural changes in the firm's workforce and skill formation strategies. First, we confirm the finding in the literature that investment spikes increase overall employment growth and productivity. We refer these effects as an "upscaling" effect as investment spikes induce firms to grow in size and productivity in their industry. Second, the increase in labor demand is met by external hiring of young skilled workers and internal training of apprentices rather than retraining incumbent workers. These

[5]Studies by Bessen et al. (2023) and Domini et al. (2021) investigate the effect of automation spikes on employment. However, these studies do not study the combination of automation with other technologies and the vintage of new automation technologies.

[6]We use the terms establishments and firms interchangeably.

effects are robust to firm size, sector, firm's age, region, and labor market tightness[7]. Event study estimates show that firms optimize skill formation strategies across time such that they hire before assessing the residual skill needs for training apprentices in subsequent period (Asphjell et al., 2014). Thus, in contexts where training demand is stable and firm-driven, technology adoption can generate employment opportunities for young workers directly (by hiring those who are skilled) and indirectly (by training those who are unskilled).

Focusing on the technological composition of the investment spike, we find that the increase in hiring of young skilled workers and training of apprentices is prominent among firms that spike in ICT and production line technologies. Effects for retraining of incumbent workers can only be found for firms that update the vintage of their existing capital. Combining hiring and training aligns with the vintage human capital model of Chari and Hopenhayn (1991) and Jovanovic and Nyarko (1996). Specifically, adoption of new technologies does not make existing human capital obsolete as firms need workers who are skilled in existing capital vintages. Since young workers are adaptable and learn new skills quickly, investment in routine-replacing technologies such as ICT and production facilities will shift skill formation towards young workers (Albinowski and Lewandowski, 2024). Retraining of incumbent workers is also an option when the relative costs of this option are low and new technologies that update existing vintages require skills that are not dissimilar to existing human capital (Müller, 2024).

This paper contributes to multiple strands of literature. First, we decompose investment spikes episodes into its technological composition and vintage characteristic. The literature on investment spikes interprets capital adjustment as embodied technological change using balance sheet data, the purchase of new equipment or investment recorded in enterprise data. Our measure of investments is analogous to those used in the literature that derives information from establishment surveys (Jensen et al., 2001). Beyond showing the difference between expansionary and replacement investments (Gourio and Kashyap, 2007; Letterie et al., 2010; Grazzi et al., 2016), there is no study that explores the constituents of capital embodied in the investment spikes. Our study adds to this literature by studying investment spikes in specific technologies and as a combination of different technologies (ICT, production line technologies, real estate and transportation systems).

Second, the investigation of the technological intensity of investment spikes contributes to the growing literature on technology adoption and its impact on firm level hiring and

[7] On one hand, existing literature confirms that old and large firms with more established internal labor markets train more apprentices (BiBB, 2022). On the other hand, smaller and younger firms have higher propensity to have an investment spike (Grazzi et al., 2016).

training decisions[8]. Recent work by Muehlemann (2024), Marydas et al. (2025) and Caselli et al. (2024) shed some light in this direction for firms in Germany, India and Italy, respectively. However, these studies use dummy variables to identify technology adoption and use instrumental variables regression approach to derive their findings. Our approach differs as we use differences-in-differences approach that is more reliable and easily identifiable. Furthermore, we directly identify the incidence and scale of technology adoption events on a longer time horizon for a large group of firms across all sectors in an advanced economy.

Third, we contribute to the training literature which documents firms' inclination to train workers and trainees in the presence of labor market imperfections (Acemoglu and Pischke, 1999a,b). We argue that new vintage of capital induces firm and technology-specificity in the skills acquired during training (Lukowski et al., 2020; Lipowski et al., 2024). For training of incumbent workers, Müller (2024) finds that investments in IT induce firms to train workers in skill intensive tasks. Participating in the apprenticeship market has been also shown to induce firms to invest in latest technologies in their production process (Rupietta and Backes-Gellner, 2019; Schultheiss and Backes-Gellner, 2020; Lipowski, 2024). We argue the other way around in that technology adoption can reinforce firm's willingness to train apprentices. Our paper is closely linked with that of Muehlemann (2024) who find that AI adoption induces training of apprentices rather than continuous training of incumbent workers. In our micro-simulation exercise, we find that investment spikes create approximately 1-1.5 percent of new training contracts every year in Germany. This shows that investment spikes are not only important for aggregate investment but also for creating new training opportunities for young people in Germany.

The rest of the paper is structured as follows. In section 2, we provide the relevant literature motivating how capital adjustment processes influence skill formation strategies in Germany. In section 3, we describe we describe our data and define investment spikes. Here we elaborate on the importance and determinants of investment spikes. In section 4, we explain our methodology. We detail the data construction for the stacked DiD setup, followed by equation formulation and entropy balancing. Section 5 provides our main results on firm's skill formation outcomes. We also provide a range of robustness checks to our empirical strategy. We provide a concluding discussion in section 6.

[8]See Aghion et al. (2022) for a systematic review of this literature

2 Background Literature

2.1 Capital adjustment and vintage human capital

Firms adjust their capital when the efficiency gains from restructuring are greater than the factor costs of using existing capital. In practice, such adjustments occur in a few, large, discrete investment episodes that are referred as investment spikes (Doms and Dunne, 1998). This is because adjustment to new capital incurs fixed costs that are irreversible and non-convex in the age of firm's existing capital (Cooper and Haltiwanger, 2006; Hamermesh and Pfann, 1996). This implies that the older the stock of capital a firm possesses, the less costly it is to introduce new capital. The literature on investment spikes attribute these adjustment costs to reflect the indivisibility of capital, increasing returns to new capital, and increasing returns to the restructuring of production activity (Cooper et al., 1999; Gourio and Kashyap, 2007)[9]. Furthermore, investment spikes have a large influence on aggregate investment. (Disney et al., 2020) show that this influence is driven by the number of firms that have a spike (extensive margin) as compared to the size of investment spike made by individual firms (intensive margin). Thus, investment spikes are significant events both at the micro and the macro level.

Investment spikes are firms' response to the risk of technological obsolescence and the need to modernize outdated machinery and equipment (Boucekkine et al., 2011). New technologies can raise efficiency by lowering the operating costs of capital. On one hand, falling capital costs may delay investment spikes, as firms wait for product prices and factor costs to stabilize (Fishman and Jovanovic, 2021). Once technological progress slows down and the cost of capital rises, owners of capital would find it optimal to replace their obsolete capital. On the other hand, positive demand and productivity shocks can trigger immediate spikes by increasing contemporaneous profits (Guo et al., 2005; Abel and Eberly, 2012). In the investment spike literature, there is inconclusive evidence regarding the performance effects of investment spikes. Some studies find that investment spikes have small and short lived positive effects on firm productivity (Power, 1998; Nilsen et al., 2008; Geylani and Stefanou, 2013; Grazzi et al., 2016) while others highlight negative effects on firm performance (Huggett and Ospina, 2001; Sakellaris, 2004; Gradzewicz, 2021). Furthermore, Jovanovic and Stolyarov (2000) argue that heterogeneity in within firm capital adjustment costs can lead to "asynchronous" investment in technologies. Since replacing old computers is cheaper than

[9] Extra-firm factors such as political shifts, protectionist policies *(reshoring)* and wider policy environment can further induce firms to concentrate their investments in a few years.

old buildings, the inter-spike hazard[10] for computers would be smaller than for buildings. From a firm life-cycle perspective, this means that younger firms would be more likely to replace low- adjustment cost technologies whereas older firms would be more likely to replace high-adjustment cost technologies[11]. Thus, firms would delay investment bursts until their capital stock is sufficiently depreciated, new technology is sufficiently advanced, and costs of adjusting to new capital are low.

In addition to newer technologies, firms can update the vintage of existing technologies. According to the "vintage human capital" model of Chari and Hopenhayn (1991), each physical capital vintage requires human capital that is partly tied to that vintage. For instance, older and more experience workers have expertise in certain tasks required to operate a specific vintage of capital. Technological progress can make such specific human capital in older vintages obsolete. Since firms use old and new technologies simultaneously, workers would slowly transition to new vintages of human capital through retraining and learning-by-doing[12]. Similarly, Jovanovic and Nyarko (1996) model firms' learning-by-doing on a given technology and the choice of when to update technology vintages. Similar to Chari and Hopenhayn, they argue that experience accumulated in old technologies does not fully transfer to new technologies creating an inertia or a "lock-in" effect. Thus, large firms with a greater vintage specificty of skills would be slow in adopting new technologies due to imperfect transferability of expertise.

Empirical work on vintage human capital posits worker demography as representative of new vintage of human capital. In their cross-country study on ICT and Robot adoption, Albinowski and Lewandowski (2024) find that technology adoption increases the demand for young workers. The loss for older workers is attributed to the lower time horizon for them to adjust their skills to new technologies. In another cross-country study, Adão et al. (2024) find that transitions to new technologies are slower if the new vintage of human capital is far from that of incumbent workers. At the occupation level, Janssen and Mohrenweiser (2018) show that an exogenous update in the required skills for an occupation due to changes in training curricula shifts labor demand from incumbents to young entrants. At the task level, Autor and Thompson (2025) find that technologies that automate an occupation's high "expertise" tasks see a decrease in wages and an increase in employment, and vice versa. This is because the remaining non-expert tasks can be performed by low-skilled individuals with lower wage

[10]Inter-spike hazard refers to the probability that a firm experiences an investment spike in a given time period, conditional on not having had a spike since the last one.

[11]To our knowledge, there are no empirical studies on the technological composition of investment spikes from a firm life-cycle perspective.

[12]In the supplementary file, we provide a conceptual model that combines investment spikes with the vintage human capital framework.

bargaining abilities. Thus, technologies that can automate vintage specific skills (typically seen in older workers) would increase the employment of young unskilled workers without increasing their wages.

2.2 Skill formation in Germany

Following an investment spike, firms must realign their workforce to meet demand for new vintage human capital. In Germany, firms have three non mutually exclusive options to build human capital : (1), hire externally, (2), train apprentices, or (3) retrain existing workers (Pfeifer and Backes-Gellner, 2018). The optimal strategy depends on the urgency of skill needs, supply of skilled labor, costs of training, and institutional setting. Conditional on the availability of skilled workers, external hiring might be the faster strategy to incorporate the new vintage of human capital into the firm's production process. However, during rapid technological progress, a skills gap might constrain external hiring due to lack of sufficiently skilled workers. Firms could also anticipate investment spikes and ex-ante adjust its workforce (Bisio et al., 2025). We use entropy balancing to control for anticipation effects.

A complementary approach is internal human capital development through apprenticeship training or firm financed further training programs for incumbent workers. In Germany, over half of each secondary school cohort enters a dual-system apprenticeship program (BiBB, 2022), combining on-the-job learning with vocational schooling. Firms create the demand for apprentice by posting vacancies and providing the necessary training infrastructure (wages, training personnel and equipment). Each apprentice receive occupation-specific training that is nationally standardized and transferable across firms (Hanushek et al., 2017). Incentives to train apprentices arise due to market imperfections that allow firms to retain trained workers at wages below their marginal productivity, capturing higher economic rents (Acemoglu and Pischke, 1999a,b). Furthermore, training apprentices acts as a screening function where apprentice productivity can be reliably measured before hiring them as skilled workers (Stevens, 1994).

Finally, firm's decision to train incumbent workers depends on the retraining potential and the nature of technology investment. Heß et al. (2023) conclude that workers in high automation-exposed jobs are significantly less likely to receive firm-sponsored further training, suggesting firms avoid investing in workers likely to be displaced by automation. Instead, training is directed toward complementary skills or workers likely to remain in reorganized roles. Concurrently, Müller (2024) show that firms investing in IT technologies increase training in high skilled tasks. However, recent work Muehlemann (2024) suggests that firms are more likely to train apprentices than its own workers after adopting artificial intelligence (AI) technologies. The difference can be explained by the skill distance between incumbent workers and new technologies. Newer technologies (such as AI and autonomous robots) could require a much different skill set for firms to invest in further training. In line with Chari and Hopenhayn (1991), updating the vintage of existing ICT technologies would induce a slow change to the optimal skills mix increasing the role of further training. We hypothesize that investment spikes are likely to trigger strategic skill adjustments, with firms selecting the most cost-effective strategy that also ensures productivity gains from the newly adopted vintage of capital.

3 Data

3.1 Linked Employer-Employee Data

Our main data source is the linked employer-employee data (LIAB) provided by the Federal Employment Agency in Germany (Ruf et al., 2021). The LIAB combines a representative establishment level survey to the administrative records of all eligible employees and apprentices working in the surveyed establishment on 30th June of a given survey year [13]. The establishment survey in the LIAB comes from the IAB Establishment Panel (EP). The EP surveys around 16,000 establishments annually with at least one employee subject to social security contributions (Bellmann et al., 2022). The sample is stratified by firm size, industry, and federal state to make it nationally representative at the establishment and workforce level. This data provides detailed information on firm characteristics and business processes including detailed information on the volume, composition, and purpose of capital investment[14]. Additionally, we have information on real daily wages, occupation, education, tenure, and labor market experience of the workers in the surveyed establishments.

Our data covers the period 2000-2019. We restrict our sample to establishments with at least seven years of information. We rely on this restriction to ensure sufficient panel observations per establishment and adequately detect the investment behavior of firms[15].

[13] We use "establishments" and "firms" interchangeably.

[14] We source information on firm age from the administrative data on establishments to account for start-ups and incumbent establishments.

[15] This restriction results in an over-sampling of medium-sized, large, manufacturing, construction, high-productivity, and training-intensive firms, and under-sampling of small and service-sector firms relative to the excluded sample. Since we use survey data as against data on financial accounts (Disney et al., 2020;

We exclude establishments in agriculture, non-profit and public administration sectors since these establishments are not profit maximizing units. We deflate all establishment-level monetary variables with industry deflators from the Federal Statistics Office. We use consumer price indices to deflate daily wage of all workers and apprentices. We derive capital stock per establishment using the modified perpetual inventory approach in (Mueller, 2008, 2017). Our final estimation sample is an unbalanced panel of approximately 13000 establishments across 20 years.

Our main outcome variables represent the three skill formation strategies used by firms to obtain new vintage of human capital: first, hiring of young workers from the external labor market, second, training apprentices, third, further training of incumbent workers. We measure hiring as the annual change in log of employment (excluding apprentices) for workers under 30 years of age[16]. We measure apprentice training as the annual change in the absolute number of apprentices being trained by the firm. Apprentices are different from employees as the former have a training contract with the establishment in which the remuneration is fixed based on collectively bargained wages (Dustmann and Schönberg, 2012). The number of apprentices and their wages reflect the scale and investments in apprenticeship training in an establishment. We measure further training as the total number of workers participating in firm financed training (excluding apprenticeships) (Hinz and Stegmaier, 2018). We follow the approach by Müller (2024) to decompose further training into training participation by skill requirement of the worker's job[17].

3.2 Identifying investment spikes

We measure firm level investments as the sum of *all* investments made by the firm in the year before the survey year. The purpose of spike identification is to account for the scaling relation between the investment rate, the size of the firm and the capital stock of the firm (Grazzi et al., 2016). Smaller firms are more likely to display higher investment rates than larger firms due to their smaller starting values (Nilsen et al., 2008). Failure to account for firm size can result in identification biases. Therefore, we use real investment per worker to define investment spikes. We define an investment spike in year τ for firm i when the

Gradzewicz, 2021), our spike identification requires the existence of large T per establishment.

[16] A limitation of our data is that we do not observe the employment biographies of workers beyond our sampled establishments. Therefore, we do not know the origin firm and job characteristics of newly hired workers as well as the destination characteristics of the laid-off workers.

[17] We categorize *low-skilled training* as training for menial jobs requiring no vocational education and *high-skilled training* as training for skilled jobs, requiring a vocational qualification or a university degree.

real investment per worker exceeds three times the leave-one-out average real investment per worker for the firm's observations period.

$$spike_{i,\tau} = \begin{cases} 1 & \text{if } \frac{I_{i,\tau}}{L_{i,\tau-1}} > 3 * \frac{1}{T-1} \sum_{t \neq \tau}^{T} \left(\frac{I_{i,t}}{L_{i,t-1}} \right), \\ 0 & \text{otherwise.} \end{cases} \tag{1}$$

where $\frac{1}{T-1} \sum_{t \neq \tau}^{T} (\frac{I_{i,t}}{L_{i,t-1}})$ is the leave-one-out average real investment per worker in the firm's observed period. For firms with multiple spikes identified by the rule in equation 1, we take the first spike in investment as our spike identifier similar to Bessen et al. (2023). This reflects the first true change in capital and assumes the subsequent spikes as complementary to the first spike. Based on equation 1, we identify more than 8,000 distinct spike events between 2001 and 2019.

Investment spikes should identify episodes where the investment rate is greater than the unconditional mean (Doms and Dunne, 1998). Thus, we use the criteria for investment per worker to be more than three times the average investment per worker. It should also imply significant reorganization in the production process of the firm. The average value of investment for firms with an investment spike is observed to be greater than €15,000 per worker (see Figure 1). This represents substantial spending equaling 40 percent of the annual earnings of full-time equivalent employed persons in Germany (Destatis, 2023). Every year around 8 percent of all firms in our sample experience an investment spike (see Table 1). These firms directly account for 25 percent of all business investments and employ 6 percent of all workers registered with the social security institutions. Despite accounting for the scaling relation between investments and firm size, we find that 75 percent of the volume of investment spikes comes from small and medium size establishments.

3.3 Determinants of investment spikes

For a better understanding of our target group of firms, we run random effects logit regression in the spirit of (Grazzi et al., 2016) to study the determinants of investment spikes. We define $spike_{i,t}$ as a binary variable coded as 1 for the year of investment spike and 0 otherwise.

$$spike_{i,t} = \beta X_{i,t-1} + \delta_t + v_i + u_{i,t} \tag{2}$$

where $X_{i,t-1}$ is a vector of exogenous variables observed in year $t-1$, δ_t is a vector of time dummies, v_i is a firm-specific unobserved random effect and $u_{i,t}$ is a serially uncorrelated logistic disturbance term. In Table 2 we show that once we control for firm age and capital stock, firm size ceases to be a determinant of investment spike (Column 2). Firms that are relatively young, with low levels of capital stock, operating at the median of the intra-industry productivity distribution and possessing obsolete state of machinery and equipment are more likely to have an investment spike (Column 7).

The results in Table 2 are consistent with the vintage capital models which suggest that firms replace obsolete capital when the productivity losses from using outdated machinery are more than than the costs of investment in newer vintages (Boucekkine et al., 2011). During rapid technological progress, replacement of older vintage of capital can achieve two objectives: first, newer capital allows firms to maintain their productivity position via quicker adaptation, and second, learning effects can be persistent by providing employees and apprentices with the new vintage of capital. These vintage capital models also argue that demand and productivity shocks can increase the likelihood of spikes by lowering the cost of capital relative to cost of labor (Guo et al., 2005; Abel and Eberly, 2012)[18]. Thus, a productivity shock in period $t-1$ can boost the likelihood of an investment spike in period t. This indicates that investment spikes are a means for major restructuring in production processes and these changes are inherently driven by firm's investment response to wider economic environment.

4 Methodology

We follow a differences-in-differences approach (DiD) to study the effect of investment spike on firm's skill formation strategies[19]. Investment spikes are heterogeneously distributed across establishments and years. Thus, we have to use a DiD approach that incorporates staggered treatment. However, recent literature on staggered DiD questions the validity of causal estimates from these methods due to staggered treatment timing and heterogeneous weights given to sub-effects (De Chaisemartin and d'Haultfoeuille, 2020; Callaway and Sant'Anna, 2021; Goodman-Bacon, 2021; Sun and Abraham, 2021; Borusyak et al., 2024). An alternative solution suggested in this literature is to use an event study design

[18]Recent work by Fishman and Jovanovic (2021) show that investment spikes can occur when the rate of technological progress slows down. This is because risk averse owners of capital are willing to invest when the risk of capital obsolescence goes down. Since risk of capital obsolescence goes down with technological progress, investment spikes are more likely when technological progress is slower.

[19]In the supplementary file, we show how naive OLS regression between investment per worker and skill formation outcomes underestimates the true effect of capital adjustment brought by investment spikes

that allows us to identify dynamic treatment effects (Baker et al., 2022)[20]. In this approach, we exploit the timing of an investment spike to avoid the concerns highlighted in the extant literature. Specifically, we deploy a stacked differences-in-differences event study design as in Bessen et al. (2023); Cengiz et al. (2019) and Goldschmidt and Schmieder (2017).

First, we identify treatment firms that had their first investment spike in year t such that $t \in [2001, 2019]$[21]. Second, firms in each treatment year are allocated to cohorts for that specific treatment year. For each cohort c, we define the event window as $\tau \in [-3, ..., 4]$. This is why we restrict our sample to establishments with at least seven years of information so that we have sufficient information on their medium-run investment behavior. Third, we supplement each cohort dataset with observations in the event window of the appropriate control group. These include firms that are never treated and not-yet or later treated. The never treated firms include all firms that do invest in the observation period but have not experienced an investment spike. The later treated firms include firms that have a treatment in $\tau + 5$ or later. For instance, in the 2007 cohort, treatment group includes firms with an investment spike in 2007 and the control include firms that have never been treated between 2004 and 2019 and firms that are treated after 2011. Finally, we stack all the cohort-specific datasets so that they line up in terms of event time τ. Due to the alignment in terms of event time across cohorts, our setting is equal to one where investment spikes would happen contemporaneously. Since each treated establishment can only go in a unique cohort, we do not suffer from past treated units contaminating our results.

Our design acts as a quasi-experiment with c sub-experiments. The average treatment effect on the treated (ATT) is thus the average of treatment effects in each of the sub-experiments. We estimate the following event study differences-in-differences specification on our stacked data:

$$Y_{j,t} = \alpha + \sum_{\tau \neq -1; \tau = -3}^{4} \beta_\tau \cdot I_\tau + \sum_{\tau \neq -1; \tau = -3}^{4} \delta_\tau \cdot I_\tau \cdot treat_j + X_{j,t} + \eta_j + \theta_t + \epsilon_{j,t} \tag{3}$$

where j indexes firms by cohort. $Y_{j,t}$ represents outcome variable such as employment growth, wage growth, apprentice growth and apprentice wage growth. I_t are leads and lags in event

[20] An advantage of using event study estimates is to see how firms adjust their skill formation strategies over time. Asphjell et al. (2014) show that factor adjustment costs dictate whether firms adjust capital and labor sequentially or simultaneously.

[21] For the treatment cohort of 2001, observations start from 2000. That is, we obtain only one lag for the treatment firms in 2001. Similarly, for the treatment cohort of 2019, we only observe information in 2020 and 2021. In our robustness checks, we restrict our sample to treatment cohorts between 2004 and 2015 so that we fully observe the leads and lags of all our treated firms.

time, with $\tau = -1$ as the reference category. β_τ captures the average effects for the control group. Treatment is defined by $treat_j = 1$ if a firm has an investment spike in the event window of the cohort. $X_{j,t}$ refers to firm size and sector fixed effects[22], η_j are cohort by firm fixed effects and θ_t are a set of calendar year fixed effects. For simplicity, we also run an equivalent two-way fixed effects specification of equation 3 as:

$$Y_{j,t} = \alpha + \delta(treat_j \times post_t) + X_{j,t} + \eta_j + \theta_t + \mu_{j,t} \tag{4}$$

where the coefficient of interest is δ. This is the average treatment effect over all post-treatment periods compared to the pre-treatment outcomes for treated firms relative to the control firms.

For a causal interpretation of δ_τ, we need to satisfy two assumptions: 1) no anticipation assumption, and 2) parallel trend assumption (Wing et al., 2024). Firm's investment as a large outlay of capital expenditure cannot be seen as completely exogenous. However, the timing of an investment spike can be considered as random when comparing two observably identical firms. Equation 3 and 4 exploit the timing by comparing treated with the not yet treated firms in the control group. This is based on the assumption that controlling for firm size and sector, treated firms only differ in their timing of the investment spike. In the supplementary file, we show that sectoral and regional proportion of firms with investment spike does not influence an individual firm's decision to have an investment spike. Additionally, we perform a plethora of placebo checks to detect anticipation in factor adjustment to corroborate the no anticipation assumption.

According to the parallel trend assumption, treated firms should not be affected by the investment spike in the absence of treatment and treated and control groups should have prallel development of outcomes in the absence of treatment. We test for the parallel trend assumption by conducting joint f-tests for lags in β_τ and δ_τ for all $\tau \in [-3, -2]$. Furthermore, we control for calendar year effects in θ_t to account for potential cyclical effects in the occurrence of investment spikes. We also show the event study plots for the control group of firms to buttress the presence of parallel trends between the treated and control group of firms. However, there could be a situation where the treatment and control group of firms, especially the never treated firms, are characteristically different. To account for such differences, we use entropy balancing to reweigh the treatment and control group based on observed variables (Hainmueller, 2012).

[22] Controlling for sector fixed effects allows us to contribute to the manufacturing specific literature on investment spikes (Geylani and Stefanou, 2013; Huggett and Ospina, 2001).

Entropy balancing uses a reweighing scheme that balances the covariates between the treatment and the control group for pre-specified moments. We include dummies for sector, size, share of workers by skill requirement and age, share of apprentices, part-time workers, female workers, log of average daily wages, region dummy, an apprenticeship training dummy, baseline firm age and capital stock (in logs) as the set of covariates. We balance these variables to their first moment. These variables are chosen to align with prior work on investments and skill demand using German establishment data by Gathmann et al. (2024) and derive from results in Table 2.

Entropy balancing provides us a few advantages over conventional matching approaches. First, matching methods restrict sample firms to matched firms based on a probabilistic score. In entropy balancing, we obtain new set of weights for the control group to align with the sampling weights of the treatment group and thus maintains sample representativeness. Second, these weights can be used with both linear and non-linear regression models. Third, computing the rebalanced weights is very efficient event with large datasets. Fourth, we can control for potential anticipation effects and ex-ante workforce adjustment by including workforce composition variables in the entropy balancing algorithm. In our stacked data, we balance the treatment and control group by cohort to avoid contamination of weights between cohorts. We show the results of entropy balancing in terms of standardized mean differences (SMD) and variance ratio for key variables in Figure 2. Since the balanced SMDs fall between the acceptable bandwidth of $[-0.1, 0.1]$ and variance ratio hovers around 1, we conclude sufficient balance in the first and the second moment of the covariate distributions.

5 Results

5.1 Investment spikes and labor demand: Upscaling or Upskilling?

We begin our findings by showing the effect of investment spikes on changes to firm employment. In figure 3, we find that investment spikes unambiguously lead to an increase in employment growth of workers (excluding apprentices). The increase in employment growth is persistent for two periods after the investment spike. TWFE estimation (equation 4) suggests that employment growth increases by approximately 2.65 percentage points (SE= 0.007) on average over the periods after the investment spike. Since the average employment growth in the control group is 2.69 percent, firms that have an investment spikes double their employment growth in the post-spike periods (0.0265/0.0269=0.982). We interpret this as evidence for an *upscaling* in the firm's workforce[23]. Our results align with the literature on investment spikes suggesting that lumpy capital adjustment is an integral upscaling phase in a firm's life cycle (Gradzewicz, 2021; Disney et al., 2020; Grazzi et al., 2016; Nilsen et al., 2008).

This upscaling coincides with a short-run increase in firm productivity (see Figure 4). We find that both output per worker and value added per worker increase following an investment spike. The average effect of investment spike is an increase of about 7 percent in the real value added per worker (SE=0.015). The higher magnitude of effect on value added per worker suggests that intermediate costs decrease by more than the increase in sales following an investment spike. Despite the increase in employment, fall in intermediate costs shows efficiency enhancing restructuring of the production process. This might be due to off-shoring of certain production processes, or process innovation that reduce overhead costs. Furthermore, the concave shaped productivity effect can further be explained by learning-by-doing processes (Jovanovic and Nyarko, 1996). Geylani and Stefanou (2013) show how learning-by-doing induced by investment spikes is a slow process and usually takes more than five years. Thus, the employment growth in the short-run does not translate into medium run increase in productivity.

We find that the *upscaling* effect does not correspond with an *upskilling* of the firm's workforce. First, we run equation 3 with the dependent variable being change in employment of workers by educational qualification and task composition[24]. In panel A of figure 5, we find a greater increase in employment growth for low and medium skilled workers compared to high skilled university educated workers. In table 3, we find that the increase in employment growth is distributed across workers in both both routine and non-routine occupations. Second, we change the dependent variable to change in average wage per worker in panel B of figure 5. Increase in average wage per worker would signify an investment spike induced wage premia for the newly hired and ability to poach workers from competitors by offering them above market clearing wage. We fail to find an increase in average wage per worker. The lack of *upskilling* conforms to the studies of Nilsen et al. (2008) and Sakellaris (2004) who argue that skill biasedness in labor demand induced by technological change might be

[23] In the supplementary file, we show that the increase in employment growth is driven by significant changes to the workforce turnover rate, that is increase in both hiring of new workers and separations of incumbent workers.

[24] We define *low skilled* workers as those without vocational qualification, *medium skilled* as those with vocational qualification and *high skilled* as those with university qualification. Furthermore, we use Dengler et al. (2014) classification of occupational tasks into *non-routine* (analytical, interactive, and manual) and *routine* (cognitive and manual) intensity.

reflected by steady investments over time rather than investment spikes [25].

5.2 Skill formation strategies

Next, we look at the channels through which firms develop new vintage of human capital that follows investment spike upscaling. Specifically, we use hiring of young workers, apprentice demand and further training as three strategies firms use to form new vintage of human capital.

5.2.1 Hiring of young skilled workers

We find that investment spikes lead to an increase in the hiring of young skilled workers (defined as skilled workers under 30 years of age). This increase occurs simultaneously with the investment spike in $t = 0$ and in $t + 4$ (see Figure 6). The average effect over post-spike periods is an increase in employment growth of 1.8 percentage points (SE = 0.007). Compared to the control mean of 0.8 percent, investment spikes increase hiring of young workers by 217 percent (0.0179/0.0082 = 2.168). Thus, we argue that investment spikes cause a large and structural change in a firm's demand for younger workers. Furthermore, the increase in the demand for young workers is largely driven by low skilled workers in $t = 0$ and medium skilled workers in $t = 4$. We again fail to find increase in the demand for high skilled workers. The hiring of young workers in $t = 4$ might suggest that firms not only hire from the external labor market, but use internally trained apprentices as skilled workers for the future (Rinawi and Backes-Gellner, 2019; Muehlemann et al., 2013)[26].

5.2.2 Apprenticeship training

The simultaneous increase in hiring of young workers (in $t = 0$) is accompanied by a sequential increase in the training of apprentices (in $t+1$). We find an increase of 6 percentage points in the change in number of apprentices trained by the firm in the year after the investment spike (see Panel A in Figure 7)[27]. However, our TWFE estimates for apprenticeship demand

[25] In the supplementary file, we provide evidence that ex-ante workforce adjustments cannot explain the lack of upskilling due to investment spikes.

[26] In supplementary file, we show that investment spikes lead to a structural change in the firm's human capital retention strategy. That is, firms increasingly retain the apprentices as skilled workers after an investment spike.

[27] In the Supplementary file, we undertake a micro-simulation of the total number of new apprentice training contracts directly created by firms with an investment spike. We find that investment spike events

is statistically insignificant. Moreover, the effect on the number of apprentices is positive yet statistically insignificant to draw conclusions about scale of training (see Panel B of Figure 7. This suggests that investment spikes only cause a transitory shock to firm's demand for apprentices rather than a permanent scaling up of firm's training portfolio. Since apprenticeship training involves an investment commitment for three to four years, sequential hiring of apprentices arise due to : 1) residual skill demand after hiring, 2) human capital adjustment to capital adjustment costs. Following the investment spike, firms assess their long term skill demand needs that cannot be sourced from external labor market. Apprenticeship training allows them to spread the human capital adjustment costs over a long period of time by screening for skilled apprentices, building vintage specific human capital, and offering wages below worker productivity (Acemoglu and Pischke, 1999b).

5.2.3 Further training of incumbent workers

Beyond hiring of young workers and apprenticeship training, firms can stimulate skill formation by providing training to its existing workers. If the distance between old and the new vintage of human capital is low, firms can train their own workers to increase the vintage specificity of firm's human capital endowments (Kredler, 2014; Kogan et al., 2021). However, we find positive but weak effects on further training of incumbent workers (see Figure 8). Decomposing the average effect into the skill intensity of further training, we find slight positive increase in the demand for high skilled training and a decrease in the low skilled training. The lack of statistical significance between investment spikes and further training is contrary to the conclusions by Müller (2024) who, using the same data, finds a positive effect of investments in ICT on firm financed further training. This might be due to conceptually different outlooks over investments - where Müller (2024) only views investments in IT as a binary variable, we view overall investments as spikes in a firm's capital adjustment process.

5.3 Composition and vintage of capital adjustment

The theoretical literature on investment spikes emphasizes the role of composition and the purpose of capital adjustment without focusing on human capital adjustment (Letterie et al., 2010; Letterie and Pfann, 2007). Firms can not only invest in different technologies but

create approximately 150,000 new training contracts between 2001 and 2019. This comes up to about 1-1.5 percent of new training contracts every year. We also show that around two-thirds of new contracts are concentrated in trade, repair, logistics and services sector. Furthermore, federal states such as North-Rhine Westphalia and Bavaria are the prominent centers for new training contracts created by investment spikes.

also update their existing technologies with newer vintages (Acemoglu and Restrepo, 2019). In this section, we first look at the heterogeneous effect on skill formation strategies by investment spikes in different technologies. Second, we look at how investment spikes that upgrade a firms machinery and equipment differ from investment spikes that maintain the same status quo.

5.3.1 Technological composition of capital adjustment

Assuming that treated firms differ only on their treatment timing, we group treated firms into investment types. We classify treated firms between technology-specific investors (TS) or technology complementary investors (TC). This is based on prior literature that emphasizes the role of complementary changes in business process that augment the effect of technology adoption (Bresnahan et al., 2002; Bartel et al., 2007). In each year, we observe the source of investments categorized as: a) electronic data processing, information and communication technologies (*ICT*), b) furniture, fixtures, machinery and equipment for production processes (*Production*), c) transportation systems (*Transport*), and, d) real estate and buildings (*Real estate*). Firms that invest in ICT, Production or both in a given year are labeled as technology-specific investors (hereon *TS* investors). Firms that complement ICT and Production investments with investments in either transport or real estate or both are defined as technology-complementary investors (hereon *TC* investors). Both TS and TC are mutually exclusive categories that represent more than 60 percent of all investment spike events[28].

Each type of investor is then a treated firm with the control group being never treated and not yet treated investors in the same category of investment. We use entropy balancing to achieve covariate balance between the treated sub-group of firms and the control sub-group of firms. We perform two-way fixed effects estimation for investor type I with the same set of outcome variables Y_{it}:

$$Y_{i,t} = \alpha + \beta_I \times (treat_{i,I} Xpost_{t,I}) + \eta_j + \theta_t + X_{i,t} + \epsilon_{i,t} \tag{5}$$

Where, $treat_{i,I} Xpost_{t,I}$ is the post treatment indicator for firm i in treatment sub-group I. The coefficient of interest is β_I which shows the average treatment effect on the treated firms that had an investment spike of type I (TS or TC investors). Equation 5 allows us to directly contribute to the literature on technology adoption where studies have uses automation spikes

[28] The two categories are not mutually exhaustive as there might be some firms who have an investment spike without investments in ICT or production facilities. We show the results for this category of investors in our supplementary file.

or digitization expenditures to study the causal effect of automation/digitization on firm level outcomes (Bessen et al., 2023; Domini et al., 2021).

Firms that invest in specific technologies might differ from firms that complement technologies with investment in physical capital such as real estate. In table 4, we show how TS treated firms differ from TC treated firms. TS investors are on average smaller in size, younger in age and less training intensive (both apprenticeship and further training) than TC investors. Interestingly, TS investors have a greater share of high skilled workers than TC investors. This coincides with the higher share of service sector firms among the TS investors than TC investors. These differences are in line with the "asynchronous investment" model suggested by Jovanovic and Stolyarov (2000) where differences in adjustment costs between factor inputs would drive the occurrence of specific types of investment spikes.

We show the estimated β_I coefficient in equation 5 for a vector of outcomes in Figure 9. First, we find consistent evidence for upscaling across both the investor types albeit with weak significance for TC investors. Second, TS investors upscale using externally hired young workers and apprentices whereas TC investors do not increase their demand for young workers. Third, TS investors increase their demand for new apprentices in routine occupations whereas young workers are demanded in non-routine occupations. This suggests that the new tasks created by technology specific investments create demand for non-routine occupations that are filled by young workers from the external labor market (Albinowski and Lewandowski, 2024). Fourth, we consistently find no effect on further training of incumbent workers for both TS and TC investors.

We find that technology intensive investments have a net positive impact on employment. A large share of this employment is concentrated among young workers and apprentices. Combining complementary investments with technology specific investments produces the largest increase in apprentice demand. Since we control for firm size and sector, these effects are not sensitive to the scale of investment spikes. Furthermore, both TS and TC investors see an increase in their productivity after the investment spike highlighting the role of capital adjustment in achieving catch-up growth. Our results conform to the vast literature on workforce adaptation of technology adoption. Specifically, firms tend to hire more younger workers when they invest in technologies due to their greater adaptability and newness in the vintage of human capital.

5.3.2 Vintage update of capital stock

In our data, firms report the state of their machinery and equipment as being state of the art, advanced or new (new vintage of capital) or medium and obsolete (old vintage of capital). We perform a triple interaction event study design in equation 6 as:

$$\Delta \ln Y_{j,t} = \alpha + \sum_{\tau \neq -1; \tau=-3}^{4} \beta_\tau \cdot I_\tau + \sum_{\tau \neq -1; \tau=-3}^{4} \delta_\tau \cdot I_\tau \cdot treat_j + \sum_{\tau \neq -1; \tau=-3}^{4} \lambda_\tau \cdot I_\tau \cdot (treat_j \times update_{j,\tau}) + \eta_j + \theta_t + X_{j,t} + \epsilon_{j,t} \tag{6}$$

where, $\delta_\tau + \lambda_\tau$ is the event study ATT for firms that update the vintage of their capital and δ_τ is the event study ATT for firms that do not change the vintage of their capital after an investment spike. For the latter group of firms, the state of their machinery and equipment will be absorbed by the cohort by firm fixed effect, η_j.Thus, changes to $update_{j,\tau}$ should reflect within firm changes in the vintage of machinery and equipment. Therefore, λ_τ is the differential effect of updating the vintage of capital stock for treated firms over firms that do not update the vintage of their capital stock. We show the event study plots for employment growth (overall and for young workers), apprentice demand and further training in Figure 10.

We find that updating technological state of capital increases firm sponsored further training (Müller, 2024). In Panel D of Figure 10, we find that investment spikes increase the number of incumbent workers in further training for firms that update their vintage of capital stock. Specifically, treated firms that update their capital increase further training by 5.45 percent more than treated firms that do not update their capital stock. The latter might consist of firms that always have advanced machinery or never have advanced machinery. Panel A, B and C show consistent results of investment spikes - upscaling driven by increase in hiring of young workers and apprentices.

Firms that update their vintage of capital stock only differ from other treated firms in their investment in further training. Updating the vintage of physical capital would create the demand for vintage specific human capital. The effect on further training is a vintage push effect where the demand for where firms that update tend to rely on training their own workers rather than hiring those workers from outside. Our results show the heterogeneous skill formation strategies used by firms when adjusting their capital. Specifically, investment spikes create the demand for new vintage of human capital. The technological intensity of investment spikes influences the hiring of young workers and apprentices whereas the updating of capital influences further training.

5.4 Robustness Checks

We provide several robustness checks to account for methodological and sampling biases in our study[29]. We keep the same set of four variables: employment growth, apprenticeship training growth, employment growth of young workers and further training of incumbent workers as outcome variables in all our tests. First, we change the definition of the investment spike and perform several placebo checks to motivate our identification of investment spike events and compliance with the SUTVA assumption for stacked DiD. Second, we test for the robustness of our estimation strategy. For this purpose, we cluster standard errors at the establishment level instead of the cohort by establishment level, check for omitted variable bias and perform Romano-Wolf step wise correction to account for multiple hypothesis testing induced bias. We find that our results are robust to such efficiency checks.

Staggered treatment designs repeatedly suffer from treatment contamination problems (Baker et al., 2022). Furthermore, the plethora of estimation procedures in the literature necessitate us to test the robustness of our stacked DiD estimator with the ones available in the literature. To test for treatment contamination, we run separate estimations of equation 3 and limit the composition of the control group to be either never treated establishments or not-yet treated establishments or both. To test for methodological alternatives, we test our stacked estimator with the imputation approach of Borusyak et al. (2024), interaction weighted estimator of Sun and Abraham (2021) and the doubly robust DiD estimator as in Callaway and Sant'Anna (2021). Regarding control group composition, we find that our main effects are robust to comparing treated firms with either never treated or not-yet treated. In supplementary file, we show that our main results are robust to all but the Callaway and Sant'Anna (2021) model. We argue that the difference arises due to the matching approach used in the two analysis. Where we use entropy balancing, Callaway and co authors use inverse probability weighting.

Finally, we perform several checks to account for sampling bias in our main results. A potential issue in our data construction was the restriction that we only include firms with at least seven years of panel observations. This restriction is a threat to the external validity of our study if the excluded firms are notionally different form the included firms. Furthermore, in our stacked setup we only have firm year observations between 2000 and 2019. This means

[29] Please refer to the Supplementary File for a detailed discussion on the robustness checks

that firms that had an investment spike between 2001 and 2003 or between 2016 and 2019 would not have sufficient observations for leads and lags. We approach these two problems as follows: first, we show a descriptives table to elucidate the raw observable differences in key firm characteristics between included firms and excluded firms. Second, we reweigh the sample to make the included firms representative of the national register of firms and run the reweighted analysis. Third, we additionally run our analysis for treatment cohorts 2004-2015 for sufficiency in observing leads and lags. Fourth, we split our sample to firms that had an investment spike in the 2000s (2001-2009) and firms that had an investment spike in the 2010s (2010-2019) to test for sampling heterogeneity. The results for sampling robustness can be seen in the Supplementary File[30].

6 Conclusion

This paper shows the effect of technology-related investment spikes on firm's decision to hire and train workers and apprentices. While prior research has documented the reallocation of skill demand due to technology adoption, fewer studies have explored the strategies that allow firms to develop and allocate its skill demand. Using twenty years of firm level data in Germany, we start by identifying investment spike episodes that signal a structural change in the firm's capital stock. Investment spikes predominantly occur in small and medium-sized firms with outdated machinery, lower capital stock, and good productivity status. Our empirical approach exploits the timing of such investment spikes whilst controlling for observable characteristics between the firms with investment spike and firms that never had a spike or did not yet have a spike. We find that investment spikes lead to an upscaling in the firm size and productivity. The increase in employment is driven by an increase in both routine and non-routine workers. The strategies used by firms to meet the increase in labor demand consist of a combination of hiring younger workers and training apprentices.

We find that firms with investments in ICT and production line technologies upscale by using external hiring and apprentices in their workforce. This is specially seen for non-routine young skilled workers who see a large increase in hiring after a technology specific investment spike. Firms that combine technological investments with real estate expansion (like adding an extra factory) or transportation systems tend to train apprentices rather than hire young workers externally. These firms train more apprentices in routine intensive occupations than in non-routine intensive occupations. Additional to hiring and apprentice training, firms that

[30]Readers can request the supplementary file by sending an email to the author at mantej.pardesi@maastrichtuniversity.nl

update the technological state of their capital stock actively retrain its incumbent workforce. We explain these results with different models of vintage human capital models and factor adjustment costs (Chari and Hopenhayn, 1991; Jovanovic and Nyarko, 1996; Jovanovic and Stolyarov, 2000).

Our study has several implications. First, it highlights the role of technology-intensive investment spikes in driving employment growth and skill formation. This is relevant as recent advances in artificial intelligence, robotics, and other digital technologies has prompted governments to incentivize large-scale corporate investments in such technologies. For instance, Germany pledged over USD 15 billion in 2023 in AI related investments, placing it just behind the United States and China in AI related investments (The Economist, 2024). Second, we emphasize on the portfolio of skill formation strategies firms use when they introduce new technologies. This strategic perspective provides a comprehensive picture of human capital responses by firms due to technology adoption (Ciarli et al., 2021). Third, the results underscore the importance of apprenticeships in facilitating firm-level adaptation to technological change, especially in skill-intensive tasks. This is especially important for the countries with vocational education systems where school-to-work transition occurs via combination of school-based and firm-based learning. Since these systems have been shown to promote technology diffusion (Rupietta and Backes-Gellner, 2019), our study shows that technology adoption and vintage updates reinforces firm's involvement in the apprenticeship system. Our study shows that investment spikes are not only technology diffusion events but also major human capital development events.

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Tables

Table 1: Importance of investment spikes in the aggregate economy (2000-2019)

Year	N_s/N	E_s/E	I_s/I	IS_s/I_s	IM_s/I_s	ITS_s/I_s	ITC_s/I_s
2000	0.130	0.100	0.146	0.335	0.396	0.147	0.508
2001	0.084	0.064	0.208	0.271	0.420	0.263	0.454
2002	0.124	0.108	0.326	0.407	0.334	0.261	0.428
2003	0.094	0.077	0.249	0.361	0.395	0.222	0.391
2004	0.089	0.072	0.205	0.406	0.408	0.273	0.416
2005	0.082	0.066	0.275	0.471	0.402	0.132	0.544
2006	0.094	0.074	0.371	0.266	0.348	0.368	0.319
2007	0.082	0.071	0.405	0.175	0.665	0.095	0.733
2008	0.083	0.068	0.261	0.409	0.313	0.157	0.398
2009	0.076	0.055	0.281	0.351	0.362	0.318	0.376
2010	0.074	0.061	0.304	0.293	0.402	0.211	0.499
2011	0.079	0.065	0.301	0.261	0.454	0.127	0.432
2012	0.071	0.053	0.175	0.354	0.494	0.200	0.419
2013	0.063	0.046	0.162	0.329	0.531	0.270	0.370
2014	0.065	0.050	0.232	0.366	0.504	0.151	0.459
2015	0.068	0.055	0.236	0.466	0.464	0.158	0.545
2016	0.075	0.058	0.180	0.312	0.545	0.209	0.309
2017	0.078	0.058	0.233	0.334	0.414	0.255	0.364
2018	0.075	0.057	0.220	0.238	0.583	0.258	0.275
2019	0.047	0.031	0.159	0.330	0.503	0.292	0.421
Average	0.082	0.064	0.246	0.337	0.447	0.218	0.433

Note: N_s/N: Share of firms with an investment spike out of all firms. E_s/E: Employment share of spike firms. I_s/I: Investment share of spike firms. IS_s/I_s: Investment share of small firms with investment spike. IM_s/I_s: Investment share of medium sized firms with investment spike. ITS_s/I_s: Investment share of technology specific investors. ITC_s/I_s : Investment share of technology complementary investors. All ratios are computed using sample weights. *Data Source:* LIAB Cross-Section Module 2000-2019.
(Back to section 3)

Table 2: Determinants of Investment Spikes

Dependent Variable: Investment Spike (1 or 0)							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Firm size ($t-1$)	-.087***	-.008	-.007	.001	.036*	.028	.028
	(.006)	(.009)	(.009)	(.010)	(.017)	(.018)	(.018)
Firm Age ($t-1$)	-.012***	-.012***	-.013***	-.013***	-.016***	-.016***	-.016***
	(.001)	(.001)	(.001)	(.001)	(.002)	(.002)	(.002)
Capital Stock ($t-1$)		-.084***	-.079***	-.087***	-.096***	-.102***	-.104***
		(.006)	(.007)	(.007)	(.020)	(.017)	(.017)
State of technical equipment ($t-1$): Average			-.178**	-.182*	-.179	-.184	-.183
			(.067)	(.072)	(.097)	(.105)	(.105)
State of technical equipment ($t-1$): New and advanced			-.304***	-.296***	-.337***	-.358***	-.359***
			(.064)	(.069)	(.096)	(.104)	(.104)
Profitability ($t-1$): Satisfactory				.043	.115	.094	.090
				(.051)	(.086)	(.092)	(.092)
Profitability ($t-1$): Very Good				.093	.174*	.154	.150
				(.052)	(.086)	(.092)	(.092)
Competitive Pressure ($t-1$): Average					.032	.006	.006
					(.051)	(.055)	(.055)
Competitive Pressure ($t-1$): High					.026	.007	-.056
					(.051)	(.056)	(.056)
Firm Productivity ($t-1$)						.031	
						(.026)	
Median productivity ($t-1$):							.091*
							(.045)
Frontier firm ($t-1$)							.075
							(.060)
N	126181	116687	109767	98991	61830	52733	52733

Note: Coefficient estimates from a random effects logit regression with robust standard errors. All regressions control for year, sector and region (*Lander*) fixed effects. Base category for the independent variables consists of firms with old and outdated machinery with deficient profits, low competitive pressure, non-exporting, and productivity laggards. Standard errors in parentheses are clustered at the establishment level. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. *Data Source:* LIAB Cross-Section Module 2000-2019.
(Back to section 3)

Table 3: Effect of investment spike on demand for workers by routine task intensity

	Δ Analytical Non-Routine	Δ Interactive Non-Routine	Δ Cognitive Routine	Δ Manual Routine	Δ Manual Non-Routine	Δ Routine Workers	Δ Non-Routine Workers
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
$treat_i X post_t$	0.006	0.007	0.010	0.012**	0.005	0.015**	0.018*
	(.004)	(.004)	(.005)	(.003)	(.005)	(.005)	(.006)
DV Mean Control	0.018	0.007	0.014	0.007	0.011	0.016	0.023
Pre-trend F-Stat	0.55	1.16	2.16	0.55	0.45	1.79	0.61
N	301644	301644	301644	301644	301644	301644	301644

Note: Routine task intensity measures are based on Dengler et al. (2014). Coefficient estimates from a two-way fixed effects model that controls for firm size, sector, cohort by firm and cohort by year fixed effects. Standard errors in parentheses are clustered at the establishment level. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. *Data Source:* Stacked data of investment spike cohorts built on the LIAB Cross-Section Module 2000-2019

(Back to Section 5)

Table 4: Descriptive difference between technology-specific and technology-complementary treated firms

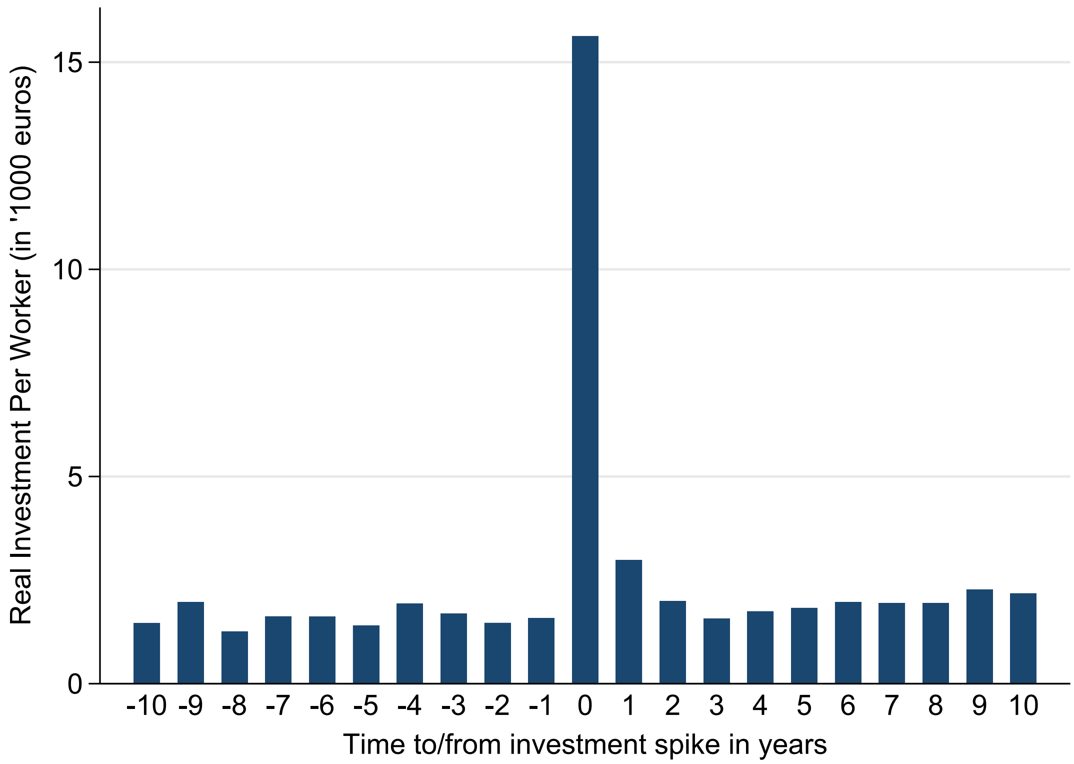
Variables	**Technology Specific**		**Technology Complementary**	
	Mean	SD	Mean	SD
Investment Spike (in thousand €)	9.865	(45.727)	26.685	(81.025)
Replacement Intensity	0.737	(0.385)	0.645	(0.384)
Firm Size	10.637	(35.124)	26.588	(113.761)
Capital Stock (in million €)	0.599	(6.620)	3.610	(31.40)
Firm Age	17.992	(10.794)	20.352	(11.849)
Apprenticeship Training	0.213	(0.410)	0.376	(0.484)
Further Training	0.511	(0.500)	0.642	(0.480)
Share of Workers:				
Low skilled	0.090	(0.179)	0.074	(0.130)
Medium skilled	0.766	(0.276)	0.796	(0.228)
High skilled	0.125	(0.235)	0.109	(0.192)
Sector:				
Consumer goods manufacturing	0.047	(0.211)	0.045	(0.207)
Industrial goods manufacturing	0.078	(0.268)	0.114	(0.318)
Mining and Construction	0.069	(0.254)	0.149	(0.356)
Trade, Repair and Logistics	0.256	(0.437)	0.293	(0.455)
Services	0.322	(0.467)	0.255	(0.436)
Education and Health	0.228	(0.419)	0.144	(0.351)
N	31,136		21,200	

Note: Summary statistics for firms that are in the estimation sample weighted by sample weights. Both technology specific and technology complementary investors are treated firms with an investment spike between 2000 and 2019. *Data Source:* LIAB Cross-Section Module 2000-2019.

(Back to Section 5)

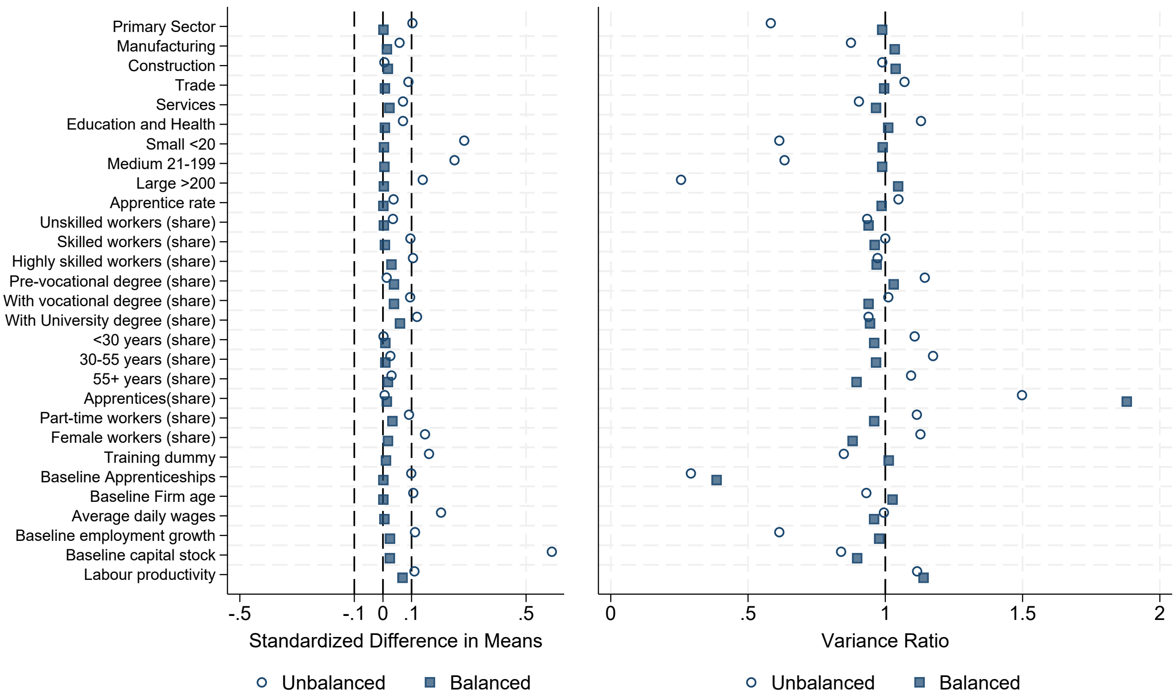
Figures

Figure 1: Distribution of investments among firms with an investment spike



Note: Real investment per worker deflated with 2015 base prices as industry deflators. Investment spike at $t = 0$. *Data Source:* LIAB Cross-Section Module 2000-2019.
(Back to Section 3)

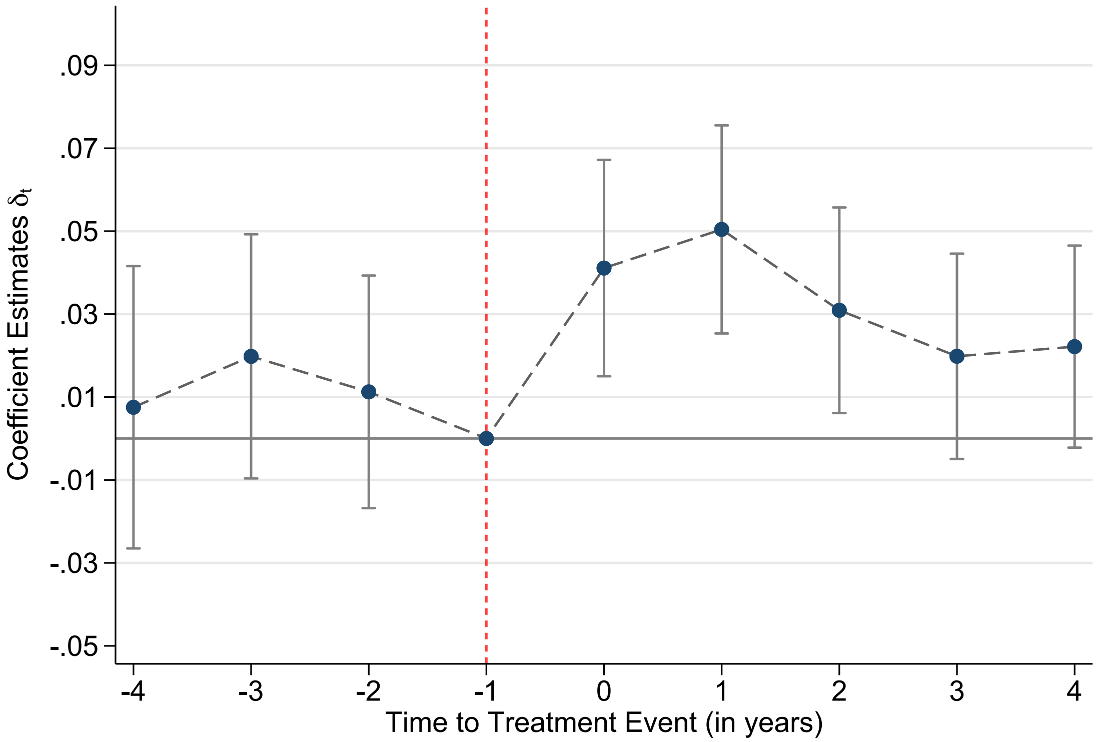
Figure 2: Balancing check between treatment and control group



Note: Covariate distribution of key firm observables balanced on first moments of treatment and control group. We show standardized difference in means (SDM) and variance ratio as tests for balancing. Variables whose SDM lies between -0.1 and 0.1 and variance ratio is approximately 1 are considered to be balanced. *Data Source:* LIAB Cross-Section Module 2000-2019.

(Back to Section 4)

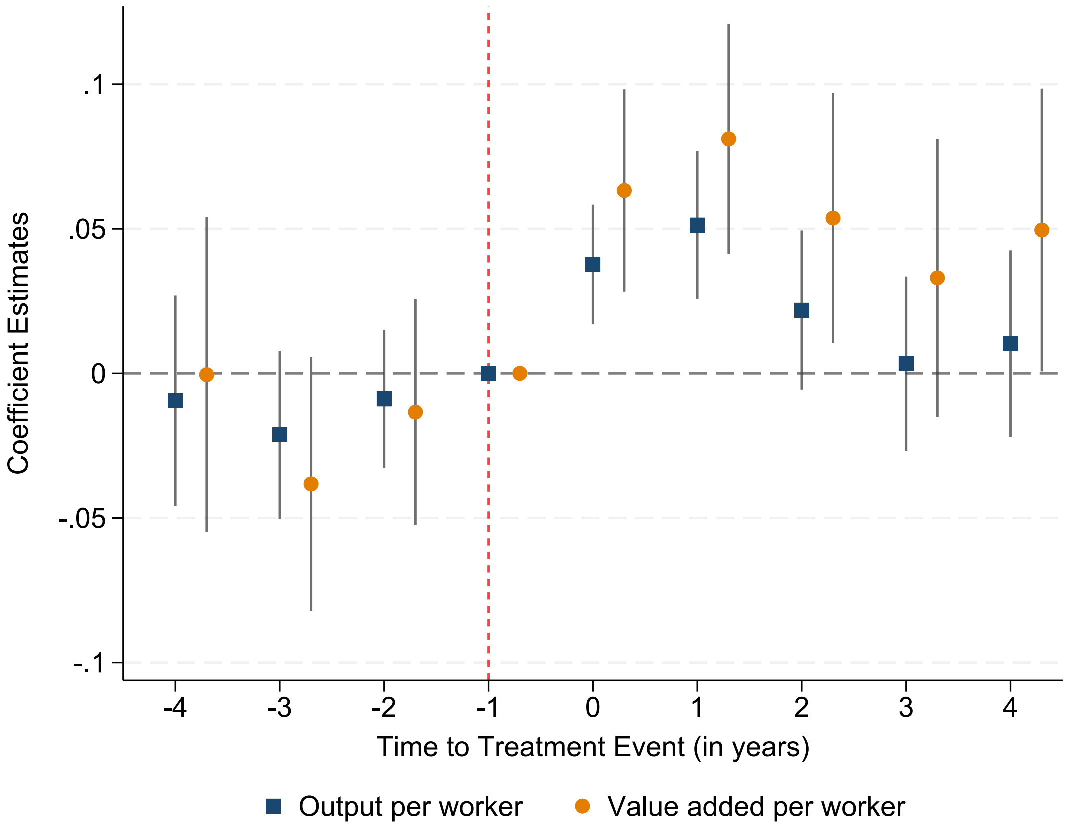
Figure 3: Effect of investment spike on employment growth



Note: Outcome variable: Δ Log of Employment (excluding apprentices). DV Mean Control = 0.027, Pre-trend F statistic = 0.600, TWFE Estimate = 0.026 (SE=0.007). Event study plot from a stacked Diff-in-Diff estimation. Treatment and control groups are reweighed using entropy balancing. Control group comprises of not-yet treated and never treated establishments. Standard errors clustered at the establishment level. 95% confidence intervals displayed. *Data Source:* Stacked data of investment spike cohorts built on the LIAB Cross-Section Module 2000-2019

(Back to Section 5)

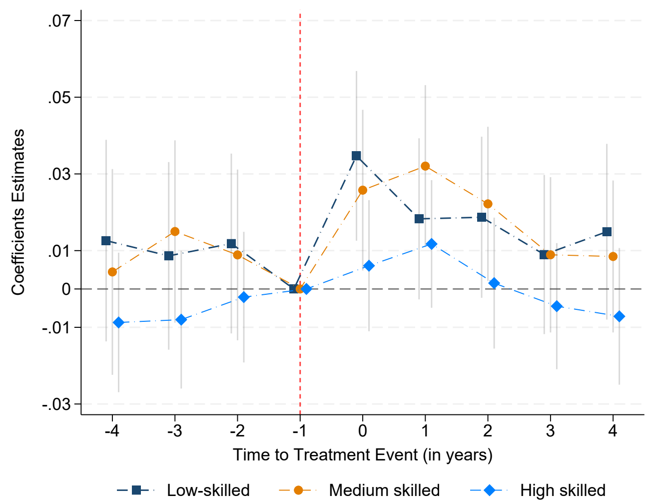
Figure 4: Effect of investment spike on firm productivity



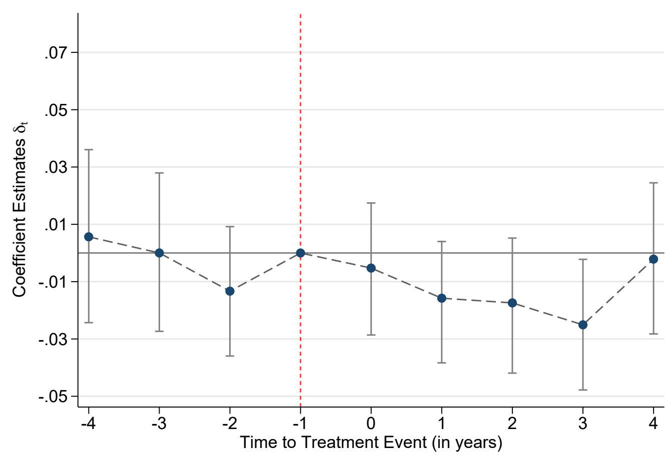
Note: Outcome variable: Log of Output per worker/Value added per worker. Event study plot from a stacked Diff-in-Diff estimation. Treatment and control groups are reweighed using entropy balancing. Control group comprises of not-yet treated and never treated establishments. Standard errors clustered at the establishment level. 95% confidence intervals displayed. *Data Source:* Stacked data of investment spike cohorts built on the LIAB Cross-Section Module 2000-2019
(Back to Section 5)

Figure 5: Effect of investment spike on employment growth by workers' education and average wage per worker

A. Employment of low, medium and high skilled workers



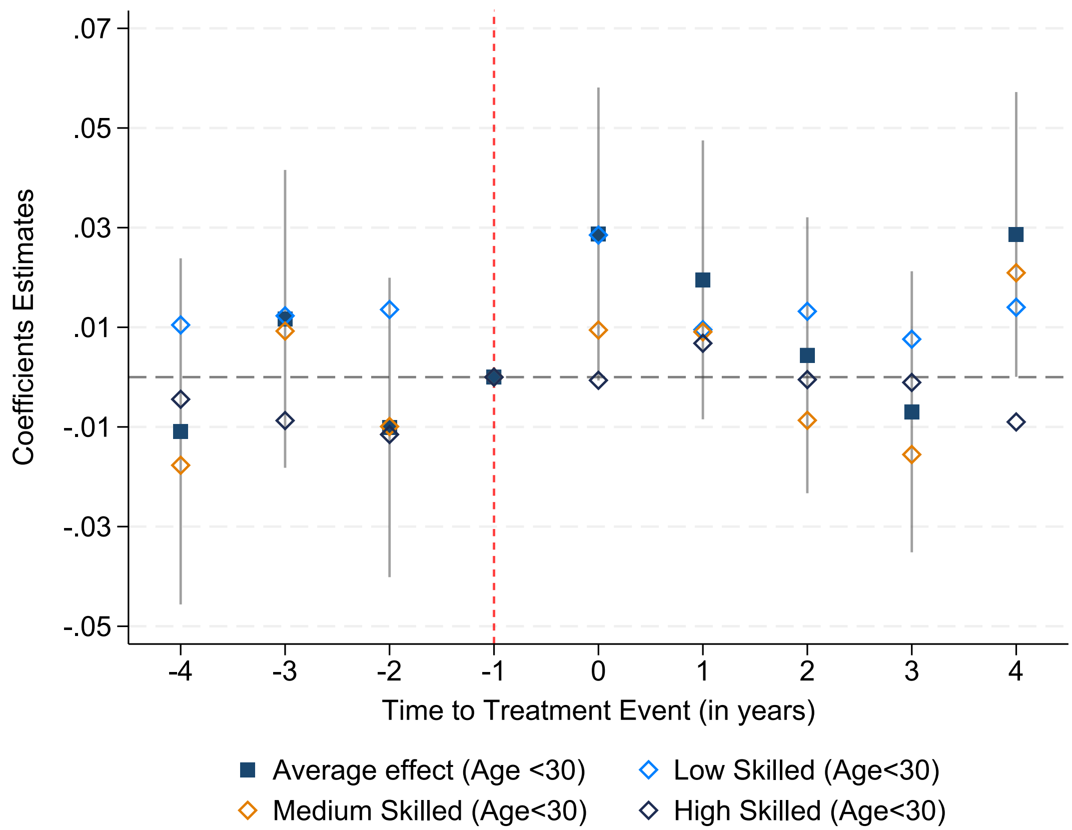
B. Average wage per worker



Note: Outcome Variable : (Panel A) Δ Log of employment by educational qualification, (Panel B) Δ Log of average wage per worker. Event study plots from stacked Diff-in-Diff estimation with entropy balancing used to match treatment with control group. Control group comprises of not-yet treated and never treated establishments. Standard errors clustered at the establishment level. 95% confidence intervals displayed. *Data Source:* Stacked data of investment spike cohorts built on the LIAB Cross-Section Module 2000-2019

(Back to Section 5)

Figure 6: Effect of investment spike on hiring of young workers from external labor market

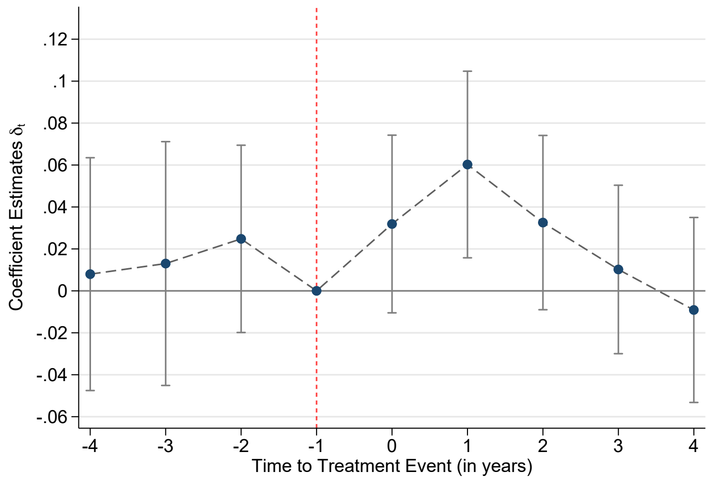


Note: Outcome variable: Δ Log of employment of workers under 30 years of age. Event study plot from a stacked Diff-in-Diff estimation. Treatment and control groups are reweighed using entropy balancing. Control group comprises of not-yet treated and never treated establishments. Standard errors clustered at the establishment level. 95% confidence intervals displayed. *Data Source:* Stacked data of investment spike cohorts built on the LIAB Cross-Section Module 2000-2019

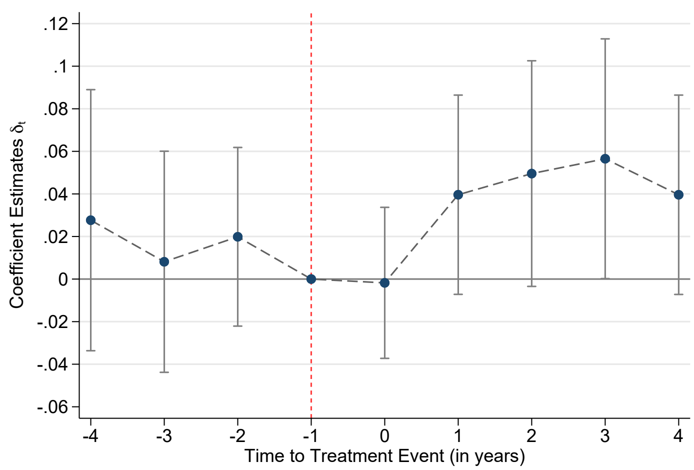
(Back to Section 5)

Figure 7: Effect of investment spike on demand for new apprentices (in differences and in levels)

A. Δ Apprentice Training



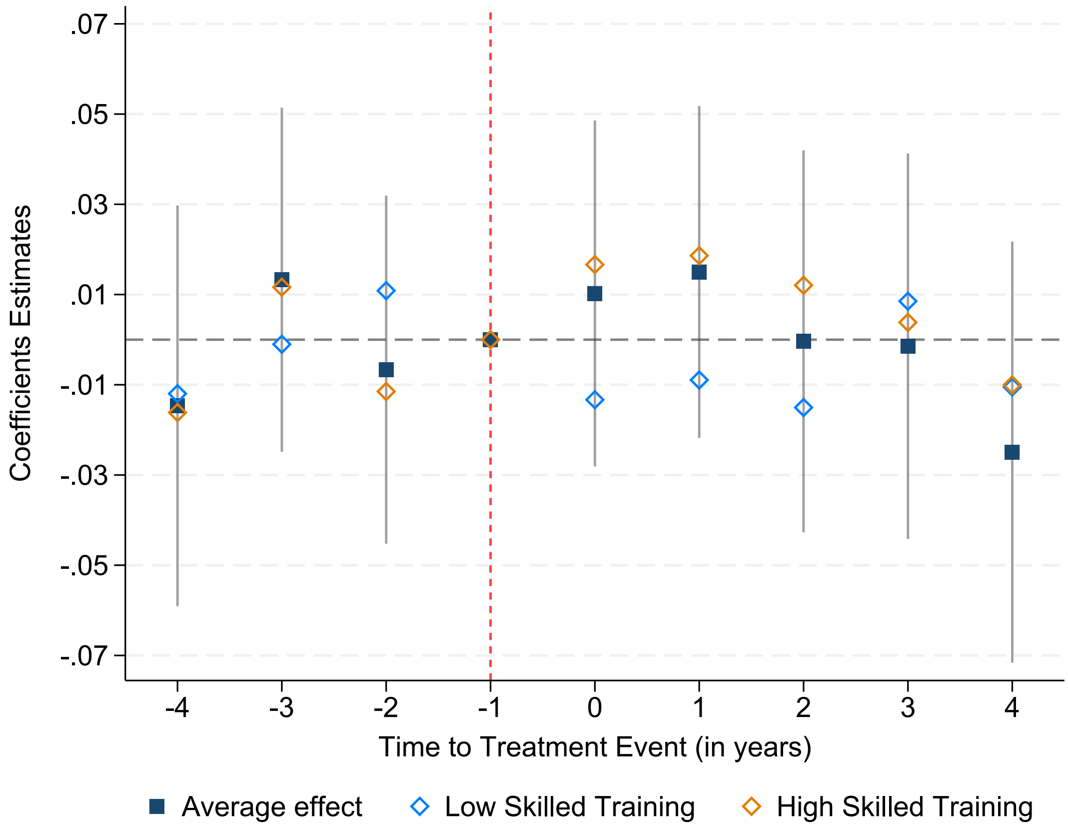
B. Apprentice Training



Note: Outcome variable: (Panel A) Δ Number of apprentices, (Panel B) Number of apprentices. Panel B is estimated using a Poisson-pseudo maximum likelihood estimator to account for count data. Graphs shown are event study plots from stacked Diff-in-Diff estimation with entropy balancing used to match treatment with control group. Control group comprises of not-yet treated and never treated establishments. Standard errors clustered at the establishment level. 95% confidence intervals displayed. *Data Source:* Stacked data of investment spike cohorts built on the LIAB Cross-Section Module 2000-2019

(Back to Section 5)

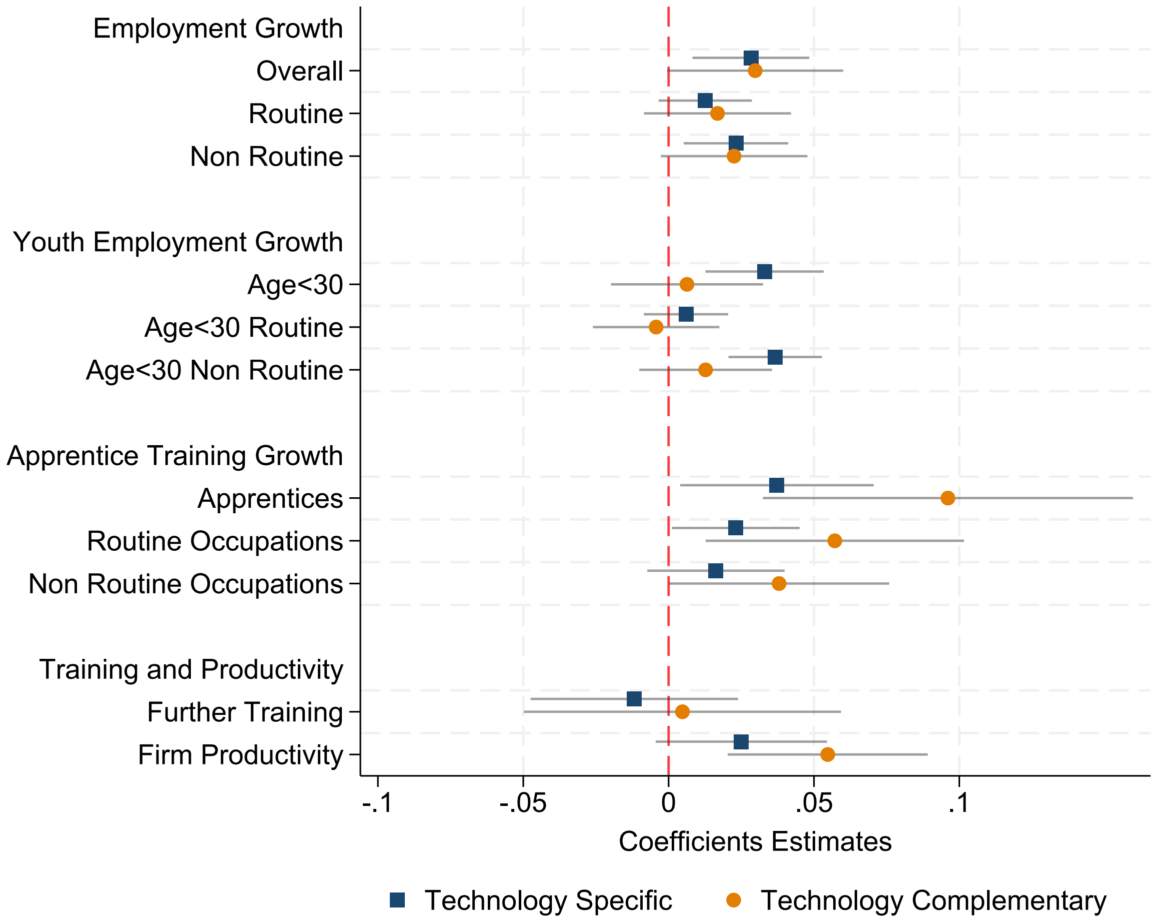
Figure 8: Effect of investment spike on further training of incumbent workers



Note: Outcome variable: Log number of workers in further training (by type of training). Event study plot from a stacked Diff-in-Diff estimation. Treatment and control groups are reweighed using entropy balancing. Control group comprises of not-yet treated and never treated establishments. Standard errors clustered at the establishment level. 95% confidence intervals displayed. *Data Source:* Stacked data of investment spike cohorts built on the LIAB Cross-Section Module 2000-2019

(Back to Section 5)

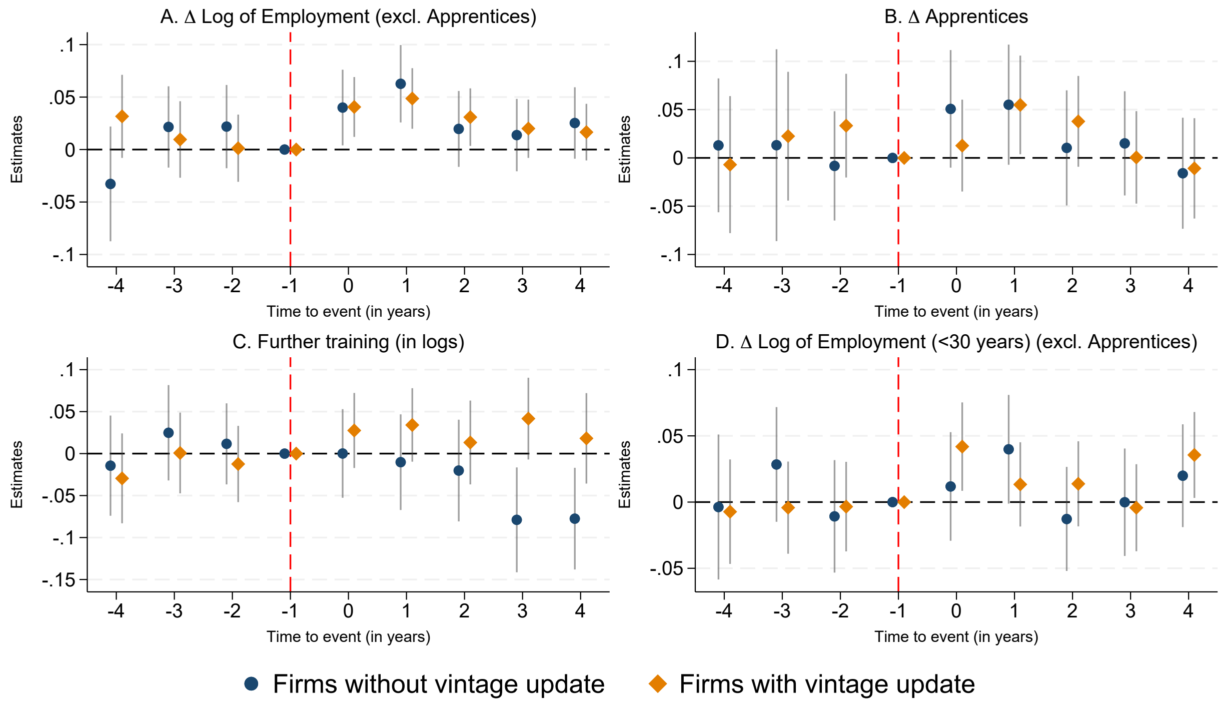
Figure 9: Effect of investment spike on key outcomes by technology-specific and technology-complementary investment spikes



Note: Graphs shown is a coefficient plot from two-way fixed effects regression estimated for technology-specific and technology complementary investors. *Technology specific* investors include IT and Production Spikes. *Technology complementary* investors include firms that make a spike in IT and Production along with real estate and transportation systems. Standard errors clustered at the establishment level. 95% confidence intervals displayed. *Data Source:* Stacked data of investment spike cohorts built on the LIAB Cross-Section Module 2000-2019

(Back to Section 5)

Figure 10: Effect of updating the vintage of capital stock on key outcome variables



Note: Event study plot from a stacked Diff-in-Diff estimation. Treatment and control groups are reweighed using entropy balancing. Control group comprises of not-yet treated and never treated establishments. Standard errors clustered at the establishment level. 95% confidence intervals displayed. *Data Source:* Stacked data of investment spike cohorts built on the LIAB Cross-Section Module 2000-2019

(Back to Section 5)