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Digital skill adoption and employment dynamics: Evidence from matched vacancy-employer–employee data[☆]

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ABSTRACT

This paper examines the interplay between firms' investments in digital skills and employment dynamics within the Danish labor market. We employ novel digital skill demand measures derived from online job postings using natural language processing techniques. We document a strong positive correlation between demand for digital skills, particularly in data science and AI, and firm productivity. Using dynamic lead–lag models, we estimate a positive relationship between digital skill investments and firm-level employment. This positive association is broad-based across demographic groups, and is stronger in certain occupations when specifically considering data science and AI skills. While digitalization drives job creation and productivity gains overall, the workforce impacts of specific technologies are heterogeneous. Our results suggest that digitalization, and particularly data science and AI adoption, may amplify existing labor market disparities across occupations, industries, and regions.

1. Introduction

The rapid advancement of digital technologies has profoundly transformed the modern workplace and labor market dynamics across industries. Automation combined with the adoption of digital tools, software, and analytical techniques is redefining skill requirements for workers and shifting the structures of many occupations (see e.g., Acemoglu, 2002; Autor et al., 2003b; Goos and Manning, 2007; Acemoglu and Autor, 2011; Beaudry and Lewis, 2014; Autor, 2015; Acemoglu and Restrepo, 2018). The digital transformation, driven by the integration of technologies ranging from productivity software to artificial intelligence (AI) into everyday business processes, has sparked significant interest in understanding the implications for employment, productivity, and the broader economy (see e.g., Brynjolfsson and McAfee, 2011, 2014; Balsmeier and Woerter, 2019).

Previous waves of digital technologies, particularly Information and Communication Technology (ICT) and industrial automation, have dramatically reshaped occupational structures, favoring skilled workers while displacing routine jobs (Autor and Dorn, 2013; Acemoglu and Restrepo, 2020). Recently, the rapid development and adoption of AI have reignited debates over whether digital technologies will augment worker productivity, or further automate and replace human labor (Autor, 2024; Brynjolfsson et al., 2025). Yet, despite substantial public and academic attention, little granular evidence exists on how firms reorganize their workforce in response to digital technology adoption, particularly across different technology types.

Digitalization and new technologies may lead to the displacement of some workers as machines and computers take over certain tasks, introducing the risk of technological unemployment (see e.g., Brynjolfsson and McAfee, 2014; Ford, 2015; Frey and Osborne, 2017). However, Autor (2015) and Acemoglu and Restrepo (2018) suggest that this potential displacement may be counterbalanced by a productivity effect: Investments in capital could lead to gains in productivity, expand market demand and the scale of production, and thereby potentially increasing the demand for labor. These "compensation mechanisms" can counteract the initial job losses from new technology and include lower production costs translating into lower prices and higher output (a productivity–price effect), the reinvestment of increased profits into expansion (creating additional labor demand), and the emergence of new tasks and roles for workers that complement the technology (Vivarelli, 2014).

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Although several studies explore the effects of ICT, automation, and AI on the labor market (e.g., Acemoglu and Restrepo, 2020; Aghion et al., 2023; Alekseeva et al., 2021; Goos, 2018), technological progress is not monolithic. Different waves of digital innovation have had distinct impacts on labor, and there is little systematic evidence on the nuanced effects of digitalization on firm-level employment dynamics; it remains unclear if and how firms reorganize their workforce in response to digitalization. This gap in the literature highlights the need for a detailed firm-level analysis that can shed light on the relationship between digitalization efforts and employment patterns within firms.

This paper addresses this gap by examining how Danish firms invest in digital skills—ranging from basic productivity software to advanced AI tools, and how these investments relate to employment and productivity outcomes at the firm level. We build on the approach by Hansen et al. (2023) and employ a novel methodological approach that leverages natural language processing techniques to extract digital skill requirements from thousands of online job postings from Denmark. This method allows us to construct detailed measures of digital skill demand at the firm level. Our approach extends the methodologies employed in previous research, such as Deming and Kahn (2018), who analyze skill requirements from job postings to understand labor market dynamics.[1] By tracking digital adoption through the precise skill demands expressed in job postings, our measures provide a granular view of digital investment that complements traditional approaches (e.g., patent data, robot sales) which often lack specificity or are limited to particular technology categories. Our data primarily captures demand for "discriminative" or "predictive" AI technologies, rather than "generative AI", which only began diffusing widely in the early 2020s and thus largely falls outside the time frame of our data.

In our unique research setting, we have access to comprehensive Danish administrative data, covering the entire population of firms and their employees. We match the employer–employee data from administrative records with our extracted skills measures from job posts. This provides an unprecedented opportunity to examine the impact of firms' investments in digital skills on employment outcomes. Our initial analysis shows a strong correlation between IT expenditures and our measures of digital skills, suggesting that firms investing in digital technologies are also prioritizing the development of a digitally skilled workforce.

We continue by focusing on two key aspects of digitalization: First, we examine how investments in digital skills, both broadly defined and specifically related to data science and AI, correlate with firm productivity and performance measures. Our results verify that our measures of digital skill demand are a meaningful representation of firms' digital adoption strategies. Second, and more importantly, we investigate the impact of digital skill investments on firm-level employment outcomes. Exploiting the longitudinal nature of our data, we employ distributed lead–lag models to capture the dynamic employment responses to changes in digital skill demand. This empirical strategy enables us to account for potential anticipation effects and delayed adjustments.

Our findings show that an increased demand for digital skills is associated with higher employment growth within firms. Specifically, a rise of 10 percentage points in the proportion of job posts seeking digital skills correlates with an increase of 0.6% in overall firm-level employment the following year. Remarkably, these gains in employment are widespread, positively affecting workers of various skill levels, job roles, demographics, and in the majority of sectors.

Nonetheless, our results also reveal significant heterogeneity in how digitalization affects the job market. Although digital skill investments promote job growth across a wide range of categories, the most substantial magnitudes are observed in occupations requiring higher levels of skill, including roles in management, professional services, technical positions, and clerical support. Moreover, the employment response of specific digital technologies, such as data science and AI, are even more focused, predominantly enhancing job opportunities in a select group of occupations and sectors.

By disaggregating the employment response across various dimensions, including skill levels, occupations, demographics, and industries, we provide insights into the heterogeneous impacts of digitalization on different segments of the workforce. Our findings contribute to the ongoing debate about the potential job displacement or job creation effects of digital technologies, shedding light on the labor market implications of firms' digital transformation strategies.

The paper is organized as follows. Section 2 provides an overview of and relates this paper to the existing literature. Section 3 describes the data. Section 4 includes our descriptive analysis. In Section 5, we present our main results on the relationship between digitalization and employment, and we discuss variations across demographics, occupations, industries, and regions. Section 6 concludes.

2. Literature review and conceptual framework

2.1. ICT adoption, digitalization, and labor markets

The initial stages of digitalization, characterized by widespread introduction of computers and information technologies within firms, had largely skill-biased impacts on the labor market (Card and DiNardo, 2002). The broad adoption of personal computers and enterprise-level software since the 1980s improved productivity but also shifted labor demand towards educated workers with advanced cognitive skills (Brynjolfsson et al., 2025). Traditional theories of skill-biased technological change (SBTC) suggest that IT capital complements more educated (higher skill) workers and raises their relative productivity. As a result, demand (and pay) rises for college-educated or otherwise "skilled" workers relative to less-educated workers. Building on this, task-based frameworks emphasize that the labor-market effects of technology depend on the routine content of tasks rather than education per se. Goos and Manning (2007), Acemoglu and Autor (2011), and Autor et al. (2008) argue that tasks classified as non-routine are inherently difficult to automate and thus tend to complement rather than substitute human labor, regardless of whether that labor is high- or low-educated. According to this view, the key distinction is the routine content of tasks, rather than simply the education or skill level of the worker performing them. The central prediction of routine-biased technological change (RBTC) is therefore job and wage polarization, characterized by employment and wage growth at the top and bottom ends of the skill distribution and a corresponding "hollowing-out" of jobs in the middle. Empirical research supports this interpretation; for instance, the diffusion of computer technologies was associated with employment polarization, decreasing mid-skilled routine jobs and increasing high-skilled professional roles and low-skilled service positions (Autor and Dorn, 2013). Autor et al. (2003b) specifically show that computing technology replaces routine clerical activities while augmenting analytical and interactive job tasks. Similarly, Bresnahan et al. (2002) document that productivity benefits from IT investments during the 1990s were strongest when accompanied by organizational adjustments and higher-skilled labor. Thus, initially, digitalization favored skilled employees, exacerbating educational wage premia and occupational polarization in developed economies.

[1] Other papers that extract information on jobs and skill demand from job posts include Modestino et al. (2016), Deming and Kahn (2018), Hershbein and Kahn (2018), Marinescu and Rathelot (2018), Grinis (2019), Adams-Prassl et al. (2023), Atalay et al. (2020), Azar et al. (2020), Blair and Deming (2020), Clemens et al. (2020), Deming and Noray (2020), Forsythe et al. (2020), Javorcik et al. (2020), Jensen (2024), Modestino et al. (2020), Alekseeva et al. (2021), Bagger et al. (2022), Daly et al. (2022), Braxton and Taska (2023) and Hansen et al. (2023). Daly et al. (2025) show that skill measures derived from job posts generally reflect skills used on the job.

Wider digitalization, defined as broad adoption of general digital technologies across sectors, also correlated positively with productivity growth (Brynjolfsson and Hitt, 2003). These innovations stimulated new tasks and entirely new professions such as IT support and data analysis, further increasing the demand for skilled labor. However, the gains from digitalization remained uneven, as many lower-skilled workers saw stagnating job prospects amid advancing automation of routine tasks. This divergence has generated ongoing discussions on whether digitalization ultimately reduces employment opportunities or creates sufficient new roles to compensate (Autor et al., 2006).

2.2. Automation and robotics: Displacement versus compensation

Parallel to digitalization, a substantial literature has developed examining the employment consequences of automation technologies, from industrial robots to algorithm-based process automation. Such technologies typically replace labor, performing tasks formerly carried out by human workers, particularly routine or manual activities. Using Dutch linked employer–employee data and a direct measure of firms' automation expenditures, Bessen et al. (2025) find that an automation "event" increases incumbent workers' separation probability and cuts days worked. These losses are concentrated in smaller firms and among older or middle-educated workers and do not arise when firms merely invest in conventional computer equipment rather than automation technologies. Similarly, Acemoglu and Restrepo (2020) provide evidence showing the adoption of industrial robots in U.S. manufacturing displaced blue-collar workers, leading to lower wages and employment levels for affected groups, while leaving the employment of higher-skilled workers largely unaffected. These findings reinforce the narrative that automation adversely affects labor demand for lower-skilled occupations. Similar displacement patterns have emerged in numerous studies, raising concerns about "technological unemployment".

Yet, the literature identifies several compensating mechanisms that may offset the initial negative employment effects of automation (Vivarelli, 2014; Vivarelli and Díaz, 2025). Economic theory outlines multiple pathways through which automation could eventually generate additional employment. First, productivity increases through innovation could lower production costs, subsequently reducing prices and boosting product demand, thus potentially increasing employment. However, this mechanism depends crucially on flexible consumer demand and competitive market conditions. Second, higher firm profits resulting from automation may be reinvested in new initiatives or technologies, stimulating further employment, provided firms indeed reinvest rather than merely accumulate surplus capital. Lastly, new technologies often lead to the emergence of entirely new products, tasks, and services that require additional labor, a mechanism historically observed across numerous sectors ranging from automotive manufacturing to computing.

Nevertheless, the net employment impact of automation remains an empirical matter, contingent upon the balance between displacement and compensation. Vivarelli (2014) argues each compensating mechanism relies on favorable market and institutional conditions, such as sufficient elasticity of demand, competitiveness, and timely reinvestment. Empirical findings reflect these nuances. For instance, the findings of Acemoglu and Restrepo (2020) suggest limited compensation in regions heavily affected by robotic automation. In contrast, Graetz and Michaels (2018), in a cross-country comparison, found that robotic adoption enhanced productivity and wages without significantly reducing total employment, indicating that economy-wide adjustments may mitigate job displacement. Ultimately, while automation can foster productivity and economic growth, its distributional effects disproportionately impact specific worker categories and geographic areas. The critical factor determining a positive net outcome appears to be the innovation-driven creation of new labor tasks, as argued by Acemoglu and Restrepo (2018).

2.3. Recent advances in AI and labor market consequences

The more recent digital technologies, comprising AI, data science, and machine learning, have reignited these debates. Unlike earlier digital technologies, AI has the capability to undertake complex cognitive functions previously reserved for skilled workers, including natural language processing, image recognition, and even decision-making support. This capability introduces the potential for automation to extend into non-routine cognitive job roles, although AI could alternatively serve as a tool that enhances rather than replaces human workers. Current literature on AI's labor market consequences is developing rapidly and includes two principal perspectives:

AI as augmentation: Several existing studies suggest that AI can enhance human labor productivity and reverse some polarization trends. Autor (2024) argues that contemporary AI has the unique potential to augment productivity for mid-skilled workers by enabling them to handle tasks traditionally performed by more specialized personnel. By synthesizing vast amounts of information rapidly and offering precise decision-making support, AI could permit nurses or physician assistants, for example, to manage complex diagnostic responsibilities or junior analysts to undertake assignments previously requiring senior expertise. Brynjolfsson et al. (2025) illustrated such augmentation, demonstrating that introducing generative AI at a Fortune 500 firm significantly increased productivity among lower-skilled and less-experienced workers by enabling them to handle more customer interactions per hour.

AI as automation: Contrastingly, other studies emphasize AI as a continuation of prior automation, potentially intensifying displacement of human labor. Applications of AI to automate cognitive tasks, such as automated customer service and algorithmic diagnostics, may replicate displacement patterns observed historically. Acemoglu (2024) argues that AI-driven automation might yield moderate productivity gains but substantial worker displacement, redistributing income away from labor towards technology owners, necessitating significant worker transitions into entirely new tasks. Evidence supporting this scenario remains mixed. While Babina et al. (2023) found that AI investment tends to concentrate in highly-skilled firms, reinforcing skill intensity and reducing mid-level management layers, widespread unemployment from AI has not yet materialized. However, the substantial increase in job postings requesting AI-related skills indicates firms are actively reshaping job roles and skill requirements (Alekseeva et al., 2021).

2.4. Measuring digital skill demand via job postings

A common challenge in studying technological adoption involves reliably measuring firm-level adoption at granular and timely levels. Traditional measures, such as IT expenditure or patent counts, remain useful but insufficiently detailed. Thus, recent research increasingly utilizes online job postings, deriving insights from firms' stated skill demands. This approach assumes firms will recruit workers proficient in the technologies they adopt, making job advertisements indicative of a firm's technological strategy. Studies by Deming and Kahn (2018), Alekseeva et al. (2021), Hansen et al. (2023), and Babina et al. (2024) demonstrated the validity of this method. This paper builds upon this tradition, using comprehensive Danish job posting data to measure the evolution of digital skills demand at the firm level over time. This measurement approach allows detailed analysis of how digital skill adoption impacts employment and productivity. Our measure identifies digital investments that call for explicit human expertise; nonetheless, vacancies in specialist clusters such as Data science & AI may reflect projects where a single specialist implements tools that may replace multiple routine tasks. Moreover, because we measure digitalization through changes in the continuous intensity of skill demand over a long period (2008–2019), we capture ongoing incremental investments, even among firms with previously established digital competencies and internal training capabilities.

2.5. Contribution of this study

This paper contributes to the existing literature in several ways. First, it introduces new firm-level indicators of digital skill adoption derived from comprehensive job posting data. Second, it provides evidence on how digital skill demand affects employment dynamics, explicitly testing whether firms investing heavily in digital skills experience job creation (consistent with productivity growth and task complementarity) or job reductions (suggesting displacement through automation). Third, by differentiating between skill categories, we directly address ongoing discussions about whether the more recent technologies, such as data science and AI, have different economic implications compared to earlier instances of ICT adoption.

This paper integrates several distinct strands of literature by examining firm-level digital skill demand and its implications for labor market outcomes. Autor and Salomons (2018) shows that the impact of technological progress on employment can look very different at the micro and macro levels. Using industry-level data across numerous countries, they find that automation directly displaces workers in the industries that implement it, but these losses are offset by gains in other industries and through higher aggregate demand. Importantly, they caution that firm-level dynamics are hidden within those industry averages: more productive (innovating) firms often grow and hire more, whereas less productive firms shrink or exit. Using detailed firm-level data from Danish job postings, we clarify how digital skill demands correlate with firm productivity and employment dynamics, offering insights into the underlying microeconomic mechanisms behind macroeconomic digitalization trends. Our contribution is to measure within-firm changes in digital-skill intensity from vacancy text and link them to firm-level employment and productivity from matched register data. Our approach exploits continuous within-firm variation in the share of vacancies requiring digital skills, capturing incremental ongoing investment. This allows us to study not only whether firms shed workers but also how they restructure hiring across skill levels, occupations, and demographic groups, a dimension not addressed in the existing firm-level literature. Therefore, our approach complements other studies such as Bessen et al. (2025), as it allows us to encompass a broader set of digital investments and include smaller firms for which data on digital investments is otherwise not readily available. In addition, linking our measure of digitalization with rich register data allows us to consider a larger set of firm level outcomes such as occupation specific employment as well as effects by different demographics (gender, immigration status, education). Our findings help reconcile mixed results in previous studies, providing empirical evidence regarding when digital investments coincide with job growth through new task creation versus when they lead to employment restructuring or downsizing. This evidence is particularly relevant for policymakers and businesses navigating digital transformation and its implications for employment and productivity.

3. Data

This paper draws upon a unique combination of data sources that allows us to construct novel measures of firm-level digital skill demand based on job posting texts and link these measures to detailed information on firm characteristics, productivity, and employee outcomes. This unique dataset enables our comprehensive analysis of the relationship between digitalization and employment dynamics in the Danish labor market. In this section, we describe the key data sources and the steps involved in constructing our primary variables of interest.

3.1. Job postings data

We acquire comprehensive job vacancy data covering virtually all Danish online job postings from 2008 to 2019 from HBS Economics (see e.g., Daly et al., 2022; Jensen, 2024, for a description of the data). These data include firm identifiers, enabling us to match job vacancy data with register data on firms' inputs and outputs. By focusing on medium to large private sector firms (with more than 20 employees on average between 2008–2019), we analyze approximately 450,000 job posts from over 7500 distinct firms. Uniquely, this paper has access to the full text of each job posting, which allows us to directly identify the demand for digital skills from the job descriptions.[2]

To extract measures of job attributes from the text of job postings, various approaches have already been applied in existing literature. Deming and Kahn (2018) employ a keyword-based approach, identifying skill demand if posts contain one or more keywords from a predefined set. Adams-Prassl et al. (2023) use a supervised machine learning approach by applying a logistic classification model. Hansen et al. (2023) develop a classification model using the 'DistilBERT' language-processing framework to assess whether a job post mentions the option to work from home, comparing this classification with other methods used in the literature. They conclude that their methods are superior to those previously applied.

However, Hansen et al. (2023) acknowledge computational constraints as a practical limitation when implementing NLP models (such as BERT). To overcome this problem, we develop a 3-step classification procedure inspired by their work, but with additional steps to improve performance.

Step 1: As our initial step to enhance the performance of our classification procedure, we fine-tune Google's uncased BERT model for a Name Entity Recognition (NER)/token classification task. This model helps us extract words and phrases (tokens) that include any skill requirement from raw job descriptions, an approach akin to that by Lasri et al. (2023) and Zhang and Zhang (2023).[3] By extracting tokens that include skill requirements, we significantly reduce the volume of text that needs further consideration by more computationally demanding models. In this step, skills are broadly defined to include mentions of worker capabilities, encompassing both general and specific skills identified in literature (e.g., social skills, cognitive skills, and management skills), thereby limiting the number of false negatives while excluding many non-skill tokens to improve performance.

Step 2: After extracting tokens likely to include a skill requirement, we aim to classify these further into specific types of skills. Adopting a 2-layer hierarchical approach we first classify the extracted tokens as digital vs. non-digital skills using Google's uncased BERT model again.[4] Similar to Hansen et al. (2023), we train our BERT-model to predict human labels of vector representations of the outputted token from our NER-model.

Step 3: Having classified extracted skill tokens as either digital or non-digital skills, we want to further divide the digital skills into eight

[2] The skill-classification algorithm developed by Burning Glass Technologies, widely adopted in previous research, is proprietary and, to our knowledge, the exact definitions of its skill clusters are not publicly available. Nonetheless, we adopt their skill taxonomy to ensure comparability with earlier studies, and transparently outline our own algorithm.

[3] Google's BERT-model is pretrained on BookCorpus (11,038 books) as well as English Wikipedia (BERT community, 2024). Additionally, since Google's BERT-models is developed for English text, we also fine-tune another BERT-style model called Maltehb/danish-bert-botxo (Højmark-Bertelsen, 2023) to use for our NER-task on job posts in Danish. This model was originally developed and trained by Certainly (2024) and tested by Hvingelby et al. (2020); the model is pretrained on 1.6 billion Danish words from Danish Wikipedia, all Danish language text from Common Crawl, as well as text from Danish online forums and subtitles (Certainly, 2021, 2024). Our model was further trained on a dataset of 4152 sentences from job posts, of which 3799 were annotated with skill-related entities.

[4] We also include a noise category to exclude any false positives from *Step 1*. Also in *Step 2* and *Step 3*, we train and use the BERT-style model Maltehb/danish-bert-botxo on job posts in Danish (Højmark-Bertelsen, 2023; Certainly, 2024).

Table 1
Digital skill clusters.

Digital skill cluster	Description	Common occupation
Productivity software	Productivity software skills such as word and excel, Enterprise Resource Planning (ERP), Project Management Software, SAP	• Administrative occupations • Customer service
Software and programming	Programming languages such as Java, SQL, and Python	• Programmers • Software developers • Database administrators
Computer and networking support	Set up, support and manage computer systems and networks	• Network administrators • Software developers • IT User support technicians
Data science & AI	Data analysis tools like R or Stata, Big Data, Data Science, AI	• Management consultants • Economists • Statisticians • Business analysts
Digital design	Digital production, graphic design, online advertising skills	• Marketing associate professionals • Graphic designers
CRM	CRM software, such as salesforce or Microsoft dynamics	• Sales professionals • Marketing associate professionals • Customer services managers
Digital marketing	Digital marketing technologies, such as social media platforms and analytics tools, such as Google analytics	• Sales & marketing professionals • Marketing associate professionals • HR officers
Machining and manufacturing technologies	Machining and engineering software and tools such as CNC machining and computer-aided design	• Machine operators • Civil engineers • Quality control and planning engineers

Notes: Adapted from Burning Glass Technologies, Nania et al. (2019).

distinct skill clusters, following the digital skill classification by Nania et al. (2019) (see Table 1). We apply a BERT-model similar to that in *Step 2*, but allowing for classification into one of the eight different digital skill clusters or a noise category. Consequently, all extracted tokens are classified as either belonging to one of the eight digital skill clusters or as noise/non-digital skills. We map every classified token back to the original job posts to achieve a job post-level classification of digital skills. We categorize a job post into a specific digital skill cluster if it includes at least one token classified as such. Therefore, a job post could be categorized into multiple digital skill clusters if it includes tokens from multiple skill clusters.

After categorizing each job post as including a specific digital skill requirement or not, we calculate annual shares of job posts including each digital skill requirement for all firms from 2008 to 2019. Our main measure of the demand for digital skills at the firm level is the ratio of job postings requesting digital skills to the total number of vacancies posted by the firm. This measure of digital investment based on skill demand is a proxy for digital adoption; an approach similar to Deming and Kahn (2018), Alekseeva et al. (2021), Goldfarb et al. (2023), and Babina et al. (2024). Note that our "Data science & AI" skill cluster primarily captures demand for "discriminative" or "predictive" AI technologies, rather than "generative AI", which only began diffusing widely in the early 2020s and thus largely falls outside the time frame of our data. Finally, we repeat *Step 3* for non-digital/general skills extracted in *Step 2*; we focus specifically on social skills and cognitive skills.

3.2. Register data

Danish register data provide information on outcomes on the full population of Danish firms, and importantly, also links to each firm's individual employees. In the following, we describe the various registers in more detail.

3.2.1. Firm data

All Danish firms are required to report their financial activities to the Danish authorities annually; these data are available from the FIRM-register. We use data on industry, profits, turnover and sales for each firm in the private sector. Importantly, these data also include firm identifiers which allow us to link each firm with their corresponding job posting data. In addition, the firm identifiers allow us to link firms with employees. For our analysis of the impact of digitalization on firm outcomes, we drop firms operating primarily in the IT industries.[5]

3.2.2. Employee data

We use detailed monthly information on employees from 2008 onward from the BFL-register. The employee data contain information on earnings, hours worked, and occupation. To the employee data, we merge information on demographics, such as country of birth and gender, from the BEF-register. We convert the monthly information on employees to yearly full-time equivalents within each relevant category, e.g., full-time equivalents employment by women and men each year. Our analysis focuses exclusively on private sector firms, as the dataset does not contain the necessary operational metrics (e.g., sales, capital) for public institutions.

3.3. Merging job postings data and register data

Using unique firm identifiers, we merge the aggregated annual job postings data to the relevant firm-year observation in the firm register.[6] We proceed by adding the yearly data on employees and, after doing so, we drop firms with an average number of full-time equivalent employees below 20 from 2008 to 2019. We also exclude firms that never posted any job vacancy in the period. We do so to focus on firms

[5] That is firms with a JUR_HOVED_BRA_DB07-code starting with 62, 631, or 582.

[6] Not all job posts include a firm identifier directly in the job post text. For these, our data provider HBS Economics imputes firm identifiers by identifying firm names in the text of job post, and next, look up the firm name in a publicly accessible database with firm identifiers. We limit our sample to those where there is at most five letters difference between the firm name in the job post and that in the firm database. We also drop job postings from firms with more job posts than employees in a given year; this is to drop recruitment agencies posting jobs on other firms' behalf.

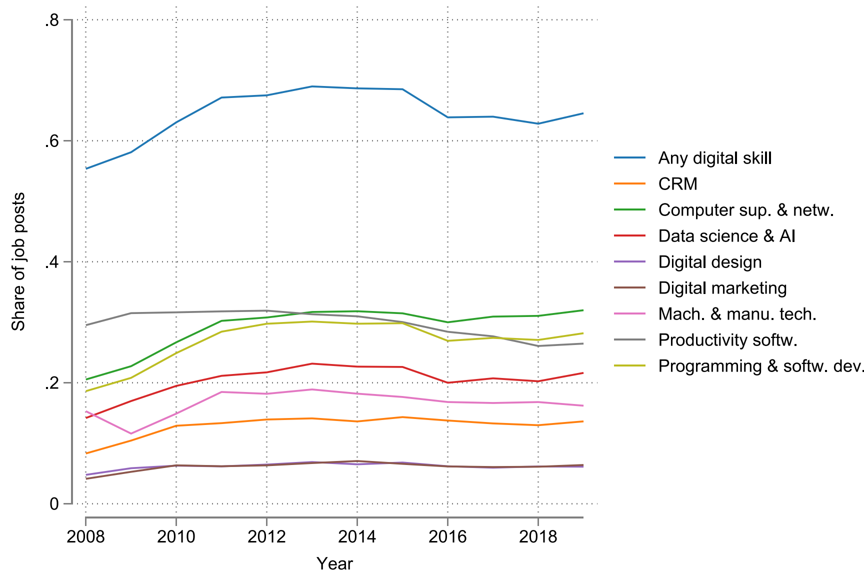

Fig. 1. The demand for digital skills.
Notes: This figure plots the annual average share of job postings that include each digital skill requirement among private-sector firms (mean employment ≥20 over 2008–2019), conditional on posting at least one vacancy in a given year.

that we observe in the job postings data, and thus, we can follow their investments in digital skills over time.

For our measures of digital skills to reflect the general population of firms, we need our job posting data to be representative of firms and workers across different segments of the labor market. In Appendix A, we verify that our data is generally representative across firm size (Fig. A.1), occupations (Figs. A.2 and A.3), and industries (Figs. A.4 and A.5). High skill occupations are slightly over-represented in the job postings data, but all occupations are well-represented in the data.

3.4. Survey data on IT expenditures of firms

To verify that our digital skill measures reflect the usage of digital technologies at the firm level, we also analyze survey data on firms regarding their IT expenditures (VITU). These data include both software and hardware expenses and are available for the years 2008–2016. By using unique firm identifiers, we can match 25% of our firm-year observations in the register data with a corresponding survey response. This matching allows us to relate IT expenses to firm size, and to calculate the fraction of IT expenses over total sales. We then compare these IT expenditure shares to the probability of demanding digital skills in job posts. However, a downside of the IT expenditure data is that firms are only surveyed in certain years, making it infeasible to construct a balanced panel and observe year-to-year variation in the level of IT expenditure. In contrast, our job posting data is available every year from 2008 through 2019, providing a more consistent source of information.

4. Descriptive analysis

In this section, we first examine the demand for digital skills across firms, industries, and over time as captured by our dataset of online job postings. Second, we describe the relationship between our measure of digital skill demand and key firm characteristics. By showing robust correlations between our digitalization measure and firm characteristics, we both provide new insights on digitalizing firms, and we confirm the relevance and significance of our digitalization measure, which paves the way for our subsequent analyses on the impact of digitalization on employment dynamics.

4.1. The demand for digital skills over time

Our sample includes approximately 450,000 job vacancies from 2008 to 2019 in firms with more than 20 employees on average, excluding the IT sector. Fig. 1 illustrates the evolution of digital skill demand in the sample over time. We find a consistently high demand for digital skills, hovering around 60% throughout. This finding aligns with other studies focusing on digital skill demand (Deming and Kahn, 2018; Nania et al., 2019; Alekseeva et al., 2021). However, there is significant heterogeneity among different sub-skills. Baseline “productivity” skills and “programming and software development” exhibit the highest demand, while “digital marketing” and “digital design” are the least demanded digital skills. The relative flatness of the “Data science & AI” line reflects the pre-generative AI period, since our data does not capture the latest “generative AI” technologies.

4.2. Firms characteristics

In Table 2, we report various summary statistics on our population of firms. We see that firms on average employ just more than a hundred full-time employees, and less than a third of those are women (because women tend to concentrate in the public sector and in smaller firms). In addition, we see that college educated workers (BA + MA + PhD) make up less than 20% of workers in the firms. Particularly important for our setting, less than 1% of employees have an IT degree (keep in mind that we exclude IT firms from our analysis). The firms are generally well established, with an age of more than 20 years on average. On average, firms post more than five jobs per year.

4.3. Digital skill demand and related firms characteristics

To examine the relationship between digital skill demand and firm characteristics, we continue by regressing the annual share of digital job posts within each firm on various firm-level characteristics. Table 3 reports the results. From Column 1, we see that firms investing in digital skills tend to be larger, employ lower proportions of foreigners, and higher proportions of women, managers, university graduates, and IT degree holders. Firms with higher levels of digital skill investments are also younger and have larger export sales.

Columns 2 and 3 further disaggregate digital job posts into those requiring “Data science & AI” skills (Column 2) and all other digital

Table 2
Firm characteristics.

	Mean	Standard deviation
Employment	103.223	402.323
Cap./emp. in 100tsd DKK	31.930	3751.424
Value added/emp. in 100tsd DKK	8.313	200.602
Share emp., foreign	0.107	0.149
Share emp., BA	0.096	0.106
Share emp., MA	0.067	0.121
Share emp., PhD	0.004	0.023
Share emp., IT degree	0.007	0.023
Share emp., manager	0.079	0.080
Share emp., female	0.288	0.225
Firm age	22.332	16.683
Exports in 100tsd DKK	1052.028	10 541.255
No. of job posts per year	5.363	33.817
Number of firms	7779	
Number of firm × year obs.	75 799	

Notes: This table reports average characteristics of firms across the sample period. All monetary values are inflation-adjusted to 2015-levels using the yearly CPI. Our data include firm-year observations from 2008–2019. We exclude firms with an average number of full-time equivalent employees below 20 from 2008 to 2019, and firms that did not post at least one job vacancy in the period.

skills (Column 3). While trends generally are similar to those in Column 1, there are differences in magnitude. For instance, firms with a larger fraction of employees with an IT degree are much less likely to invest in “Data science & AI” skills than in other digital skills. A higher share of employees with a Ph.D. degree is significantly correlated with a higher share of “Data science & AI” job posts, while it is insignificantly related to the share of other digital job posts.

4.3.1. Digital skill demand and IT expenditures

When using the demand for digital skills in job posts to measure firm-level digitalization, a key assumption is that digital skill demand reflects the adoption of digital technologies within the firm. To verify this assumption, we use firm-level survey data on IT expenditures and compare it to the share of job posts that demand digital skills. Fig. 2, Panel (a), presents this relationship for any digital skill, while Panel (b) focuses specifically on data science & AI skills. Panel (a) shows that firms with the highest share of IT expenditures are nearly 60% more likely to require digital skills in their job postings than those with the lowest share of IT expenditures. In Panel (b), we observe that firms with the highest IT expenditure shares are more than twice as likely to seek data science and AI skills compared to firms with the lowest expenditure shares. This strong correlation between IT expenditures and digital skill demand supports the validity of using job postings as an indicator of digital adoption within firms. Firms that invest heavily in IT infrastructure and systems are likely to also invest in human capital by seeking employees with the necessary digital competencies to utilize these technologies effectively. Thus, the findings in Fig. 2 suggest a strong association between IT expenditure and demand for digital skills, with a particularly strong relationship for data science & AI skills.[7]

4.4. Productivity and measures of digitalization

To further gauge the information conveyed by our measure of digitalization, we first examine the relationship between productivity and the percentage of digital job postings, our indicator of digital adoption. Through automation, optimization, and consolidation of production processes, digitalization can reduce cost and usage of resources. It also has the potential to increase consumer satisfaction, to promote the creation of new products, and to support data-driven, informed decision-making (Goldfarb and Tucker, 2019; OECD, 2019). If digital job postings successfully capture digital adoption, we would anticipate a positive correlation with productivity, given the potential for digitalization to increase corporate efficiency and performance. However, we do not attribute a causal effect to our results. Instead, our focus is on evaluating the reliability and significance of our digitalization metric. We want to ensure that our measurement reflects digital adoption rather than statistical noise.

We evaluate the relevance of our measure of digitalization by investigating if there is a correlation between digitalization and (1) labor productivity and (2) Total Factor Productivity (TFP).

4.4.1. Digitalization and labor productivity

The production function of firm i at year t is given by Eq. (1), where Y_{it} is value added, A_{it} denotes total factor productivity, K_{it} stands for the firm’s capital stock and L_{it} represents labor inputs

$$Y_{it} = A_{it} K_{it}^{\alpha} L_{it}^{\beta} \tag{1}$$

We start by assessing the relationship between digitalization and labor productivity. To do so, we modify Eq. (1) by adding our measure of digitalization, D_{it} the share of job openings that require a digital skill, to the production function.

$$Y_{it} = A_{it} K_{it}^{\alpha} L_{it}^{\beta} exp(\gamma D_{it}) \tag{2}$$

The digitalization variable is exponentiated so that it enters the production function in levels rather than in logarithmic form when log-transforming the production function.[8] Dividing Eq. (2) by labor and taking the logarithm, we can rewrite the production function as:

$$\log\left(\frac{Y_{it}}{L_{it}}\right) = \alpha \log\left(\frac{K_{it}}{L_{it}}\right) + (\beta + \alpha - 1)\log(L_{it}) + \gamma D_{it} + I_i + \tau_t + \epsilon_{it} \tag{3}$$

Here the productivity term is replaced by a set of fixed effects for the industry or firm, denoted as I_i, which includes firm-level yearly trends in the share of I.T. graduates at baseline (in 2008), four-digits industry fixed effects and industry trends. When estimating this relationship, we also include year fixed-effects τ_t and ϵ_{it} is the error term.

Table 4 presents the estimated coefficients from Eq. (3). Column 1 reveals a striking result: an increase in the share of digital job vacancies is significantly and positively related to labor productivity; a 10 percentage point rise in the share of digital job vacancies corresponds to an approximately 0.6% increase in labor productivity. To put this result in context, considering that the average share of digital vacancies in our sample is 32%, with a standard deviation of 0.42, a one standard-deviation increase in digital vacancies translates into a 2.64% ($= (exp(0.062 * 0.42) - 1) \times 100$) increase in labor productivity.

Column 2 introduces additional control variables: the share of vacancies demanding “cognitive” and “social” skills, to mitigate any potential confounding effects that might arise from overlapping skill requirements. Despite the inclusion of these variables, the coefficient for digital vacancies remains statistically significant, albeit slightly reduced in magnitude. This confirms the robustness of the positive relationship between digital vacancies and labor productivity, even when accounting for the demand for other skills.

Lastly, in Column 3, we divide digital vacancies into those that require skills related to “Data science & AI” and those requiring other digital skills. We see that the coefficient for “Data science & AI” is

[7] A potential limitation of our data is that we only observe digitalization in firms that posts jobs requiring digital skills. If firms retrain workers in-house or have already hired the necessary capacity prior to 2008, our data would miss these potentially digitalized firms. In Table A.1, we verify that the vast majority of firms are captured by the job postings data, and firms with digital job posts have substantially higher levels of IT expenditure compared to both firms that do not post jobs and firms that do post jobs, but not digital jobs.

[8] We do not log-transform the digitalization measures D_{it} because they are fractional shares with many zeros. In the production-function setup, we allow digitalization to enter multiplicatively as $\exp(\gamma D_{it})$; after taking logs, D_{it} therefore enters the estimating equation in levels.

Table 3
Digital skills and firm characteristics.

Variables	(1) Share, any digital job posts	(2) Share, data science job posts	(3) Share, other digital job posts
ln(employment)	0.100***	0.032***	0.185***
	(0.003)	(0.001)	(0.006)
Share emp., foreign	−0.091***	−0.031***	−0.206***
	(0.019)	(0.008)	(0.035)
Share emp., BA	0.243***	0.099***	0.596***
	(0.032)	(0.014)	(0.070)
Share emp., MA	0.078**	0.139***	0.316***
	(0.036)	(0.019)	(0.080)
Share emp., PhD	0.261*	0.413***	0.433
	(0.154)	(0.097)	(0.355)
Share emp., IT degree	0.664***	0.284***	2.007***
	(0.143)	(0.069)	(0.368)
ln(firm age)	−0.017***	−0.004***	−0.026***
	(0.003)	(0.001)	(0.006)
Share emp., managers	0.162***	0.061***	0.352***
	(0.032)	(0.014)	(0.068)
Share emp., female	0.046**	0.044***	0.083**
	(0.018)	(0.008)	(0.037)
ln(exports)	0.009***	0.003***	0.020***
	(0.001)	(0.000)	(0.001)
Constant	−0.094***	−0.078***	−0.275***
	(0.014)	(0.006)	(0.028)
Number of observations	74 915	74 915	74 915
Number of firms	7762	7762	7762
Adjusted R2	0.159	0.107	0.181

Notes: The table presents the results of OLS regressions conducted at the firm-year level. We retain observations with non-missing data for all firm-based variables included in the analysis. Standard errors, shown in parentheses, are clustered by firm. The dependent variables are: the share of vacancies demanding digital skills (column 1), the share of vacancies demanding "Data science & AI" skills (columns 2), and the share of vacancies demanding any digital skill other than "Data science & AI" skills (columns 3). If exports are zero, we substitute the log value with zeros and introduce binary variables that take on the value one when the original values are zero. $*** \ p < 0.01$, $** \ p < 0.05$, $* \ p < 0.1$.

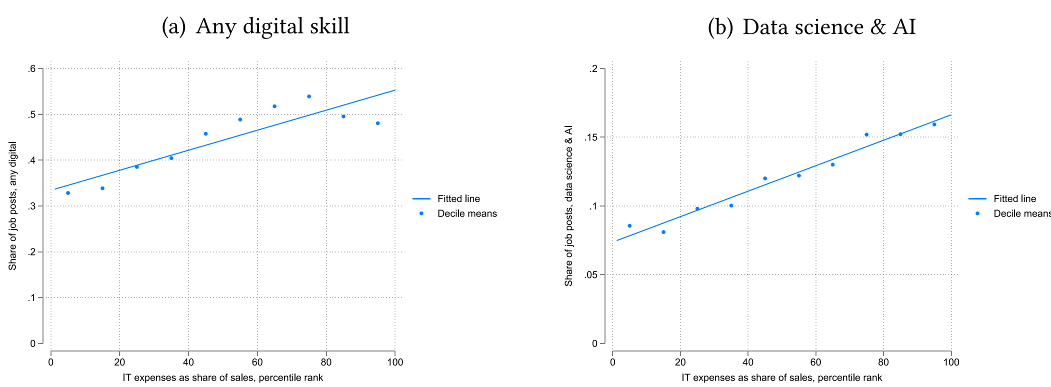

Fig. 2. Digital skill demand and IT expenditure.
Notes: This figure shows the relationship between firm-level IT expenditure and the share of job posts demanding digital skills. The x-axis shows the percentile rank of total IT expenditure over total sales. Our data include firm-year observations from 2008–2016 of firms that observed in the survey VITU. Sample sizes: 4251 firms, 14,511 firm-year observations.

significantly larger than that for other digital skills. A 10 percentage point increase in the share of digital vacancies pertaining to data science and AI corresponds to a substantial 0.63% ($= (exp(0.1 * 0.063) - 1) \times 100$) increase in labor productivity. On the contrary, other digital skills contribute to a comparatively smaller 0.24% ($= (exp(0.1 * 0.024) - 1) \times 100$) increase in labor productivity. This finding highlights the pronounced positive impact of "Data science & AI" vacancies on labor productivity compared to other digital skills.

4.4.2. Digitalization and TFP

To further explore the relevance of our measure of digitalization, we evaluate the relationship between TFP and the share of job posts demanding digital skills. To do so, we first estimate Eq. (1) (in logs) by one-digit industry using the approach suggested by Wooldridge (2009), a one-step (efficient) GMM formulation of the Levinsohn and Petrin (2003) method to estimate TFP. We follow the standard practice of using (the log of) intermediate inputs as a proxy variable in the control function and assume a third-order polynomials in the first stage. The results in Table 5 show that a 10 percentage point increase in the share of digital job posts leads to an approximate 0.88% increase in TFP (Column 1). Adding the share of job posts that require cognitive and social skills only slightly reduces the magnitude of this coefficient (Column 2). Finally, the share of job posts demanding data analysis and AI skills has a much larger magnitude than job posts requiring other digital skills (Column 3).

Table 4
Productivity.

Variables	(1) ln(value added/emp.)	(2) ln(value added/emp.)	(3) ln(value added/emp.)
ln(employment)	−0.013***	−0.014***	−0.014***
	(0.004)	(0.004)	(0.004)
ln(capital/empl.)	0.093***	0.093***	0.093***
	(0.004)	(0.004)	(0.004)
Share job posts, digital	0.062***	0.050***	
	(0.007)	(0.007)	
Share job posts, cognitive		0.066***	
		(0.010)	
Share job posts, social		0.005	
		(0.007)	
Share job posts, data science & AI			0.063***
			(0.010)
Share job posts, other digital			0.024***
			(0.003)
Constant	12.170***	12.172***	12.182***
	(0.046)	(0.046)	(0.046)
Number of observations	75 799	75 799	75 799
Number of firms	7779	7779	7779
Adjusted R2	0.306	0.307	0.307

Notes: This table shows correlations between different types of digital skill requirements in job posts and firm productivity measured by value added per worker. All regressions are estimated by OLS and standard errors are clustered at the firm-level. The regressions include controls for a set of FEs: year-by-industry (3-digit NACE), year-by-region (5 regions), and year-by-the share of employees with an IT degree in 2008. We also include an indicator variable that takes on the value 1 if the firm had no job postings in a particular year. Our data include firm-year observations from 2008–2019. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table 5
TFP and digital skills.

Variables	(1) TFP	(2) TFP	(3) TFP
Share job posts, any digital	0.088***	0.060***	
	(0.008)	(0.008)	
Share job posts, cognitive		0.113***	
		(0.011)	
Share job posts, social		0.034***	
		(0.007)	
Share job posts, data science & AI			0.101***
			(0.011)
Share job posts, other digital			0.035***
			(0.004)
Constant	13.073***	13.059***	13.075***
	(0.007)	(0.007)	(0.006)
Number of observations	75 799	75 799	75 799
Number of firms	7779	7779	7779
Adjusted R2	0.370	0.372	0.372

Notes: This table shows correlations between different types of digital skill requirements in job posts and firm-level TFP. All regressions are estimated by OLS and standard errors are clustered at the firm-level. The regressions include controls for a set of FEs: year-by-industry (3-digit NACE), year-by-region (5 regions), and year-by-the share of employees with an IT degree in 2008. We also include an indicator variable that takes on the value 1 if the firm had no job postings in a particular year. Our data include firm-year observations from 2008–2019. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Overall, our results suggest that our measures of the demand for digital skills are highly informative — as one would expect, higher digital skill demand correlates with both increased labor productivity and higher TFP.

5. Digitalization and firm-level employment

In the previous section, we validate our digital skill adoption measure in three complementary ways. First, we show that there is a strong correlation between IT expenditures and digital skill demand (Fig. 2). We also show that most firms are captured by the job postings data, and firms with digital job posts have substantially higher levels of IT expenditure compared to both firms that do not post jobs and firms that post jobs but do not post digital jobs (Table A.1). Second, we restrict the sample to firms that post at least one vacancy during the sample period to ensure that identification does not rely on firms with no hiring activity. Third, we demonstrate that our digitalization measure remains positively and significantly associated with productivity even after controlling for other skill demands and for contemporaneous employment, indicating that it does not merely proxy for overall firm expansion (Table 4).

We now turn to the relationship between digitalization and employment. In the following sections, we demonstrate that companies investing in additional digital skills experience increased total employment and sales, without any evident adverse effects on relative labor demand across skill groups, demographic segments, or occupations.

5.1. Method

To assess the impact of digitalization on employment, we estimate a series of distributed lead–lag models (similar to e.g., Schmidheiny and Siegloch, 2023). This modeling technique allows us to consider two essential aspects of digital investment. First, it accommodates the complete dynamics of firms' employment responses, accounting for the possibility of delayed or anticipated responses. Second, our empirical model acknowledges that investments in digital activities do not occur discretely but rather represent a form of lumpy investment. The lead–lag models we estimate have the following structure:

$$E_{it} = \sum_{k=-4}^{4} \delta_k D_{it-k} + \mu_i + \eta_{it} + \lambda_{srt} + \rho_{it} + \epsilon_{it} \tag{4}$$

Here, E_{it} refers to various metrics related to firm-level employment and other outcomes for firm i in year t, and D_{it-k} is a continuous treatment dosage representing the share of job advertisements requiring digital skills in $t-k$. D_{it-k} is the share of a firm's vacancies requiring digital skills, which captures composition (digital intensity) rather than scale; thus, generic firm growth in postings is absorbed by the denominator.

As the initial investment in digital technologies by a firm cannot be precisely identified, for example, if it occurred prior to the beginning of our sample period, we incorporate a trend in the baseline (in 2008) share of employment of workers with an I.T. degree (η_{it}). This adjustment allows us to account for the evolving employment landscape related to information technology, serving as a proxy for the unobservable early digital investments by firm to capture pre-existing digital maturity and baseline propensity to adopt new technologies.

The equation includes additional components: μ_i is a firm fixed effect, λ_{srt} is a year-by-industry-by-region (3-digit NACE, 5 regions) FEs, and ϵ_{it} denotes the error term. We also add an indicator variable equal to 1 in years where firms do not post any jobs, ρ_{it}. This formulation allows us to comprehensively analyze the relationship between digitalization and employment, considering both temporal dynamics and the nature of digital investments. In this model, δ_k quantifies the employment response to digital investment at $t-k$, accounting for the influence of both past and future investments. To identify the model, the following condition must hold:

$$E[D_{i,t-k} \cdot \epsilon_{it} | \mu_i, \lambda_{srt}] = 0, \forall (t, k) \tag{5}$$

The coefficients estimated for the lead terms (i.e., δ_k where $k < 0$) can be used to conduct a standard pre-trend falsification test. This test evaluates the validity of the model by checking if there is a systematic relationship between a firm's digital investments and its employment levels in future years before the investment occurred. Such a relationship would indicate that the firm adjusted its employment in anticipation of the digital investment, violating the model's assumptions.

Throughout the remainder of the paper, we will present two sets of results. First, we will show results when the variable D_{it} measures the share of job postings requiring any digital skill. Subsequently, we will show results for the share of job postings specifically demanding data science and AI skills. We make this distinction because we documented a particularly strong relationship between "Data science & AI" skills and productivity in Section 4.4.

Our framework involves two main assumptions to identify the employment response to digital skill adoption. First, our distributed lag design relies on no anticipation effects, requiring that firms do not systematically adjust employment in anticipation of a future increase in digital skill demand. As Baker et al. (2026) note, this assumption is testable through pre-trend analysis but not fully verifiable. In our context, it is partially limited by the nature of digital transformation, which is typically a planned process: firms may begin workforce adjustments before the observable shift in vacancy composition is captured in our data. The flat pre-period coefficients in Figs. 3 and 4 are consistent with the assumption conditional on our fixed effects, but cannot rule out smooth anticipatory adjustment absorbed into baseline levels. Importantly, if anticipatory hiring precedes the measured treatment, our post-period estimates would be downward-biased, suggesting our reported associations are conservative lower bounds. We therefore interpret our results as capturing the employment dynamics observable around the measured digital skill investment rather than the full adjustment from its strategic origin.

Second, the estimation of these lag-lead models with two-way fixed effects carry an assumption of homogeneous treatment effects across cohorts, an assumption recently shown to be restrictive and potentially problematic (e.g., Callaway and Sant'Anna, 2021). The core issue is that standard two-way fixed-effects estimators can lead to biased estimates ("forbidden comparisons") when treatment effects differ across cohorts or vary over time. To assess the robustness of our findings against this concern, we implement an alternative estimation strategy following Bessen et al. (2025), a stacked difference-in-differences approach that explicitly relaxes the assumption of homogeneous treatment effects. Because this method significantly reduces the sample size by dropping firms without clear treatment timing, we report it in Appendix B rather than in the main text. Importantly, the results obtained using the Bessen et al. (2025) estimation method are consistent with our main estimates, reinforcing the credibility of our primary approach despite the potential methodological limitations.

5.2. Digitalization and employment

Fig. 3 presents our lead–lag estimates that illustrate the impact of investing in digital skills on various employment measures at firms with more than 20 employees. We initially analyze the relationship between digitalization and overall labor demand in Panel (a). The employment trend before the investment is generally flat, hovering around zero. Notably, we find that employment increases at firms that invest more in digital skills. The semi-elasticity of firm employment with respect to the digital investment event rises after the investment. Specifically, a 10-percentage point increase in the share of digital job advertisements results in a 0.2% increase in employment in the investment year, peaking at 0.6% in the first year following the investment. This level is sustained until the end of the outcome window. The flat pre-trend centered around zero, combined with the pronounced upward shift post-investment, suggests a positive relationship between digital skill investments and firm employment, with no significant evidence of anticipation effects.[9] We repeat this regression for subcategories of employment, focusing on the employment of women (Panel b), immigrants (Panel c), and university graduates (Panel d) as outcomes. The findings align with those for overall employment, as the pre-trend remains flat, and higher shares of investment in digital skills translate into increases in the employment of each sub-category during our estimation window. Panel (e) illustrates the firm's total sales and value-added responses. Both measures experience an increase after the investment, showing a semi-elasticity of 0.03 on impact and remaining at elevated levels during our estimation window. These patterns confirm the scale effect resulting from increased productivity through investments in digital skills. Finally, we also plot the labor share and labor churning in Panels (g) and (h), respectively.[10] Investment in digital skills does not show a significant relationship with the labor share but is associated with a short-lived increase in labor churning, suggesting that some employees may be replaced by new hires.

Next, Fig. 4 replicates the analysis from Fig. 3, but focusing specifically on data science and AI skills rather than general digitalization. We make this distinction due to the stronger correlation between this specific type of digitalization and productivity, as presented in Section 4.4. Panels (a) through (d) presents the results of the lead–lag model with different employment categories as outcomes.

Again, we find a positive relationship between the employment and higher shares of data science and AI job posts. Similarly, sales and value-added exhibit marked increases after the adoption of data science and AI skills. Finally, our results indicate no discernible relationship between data science and AI skill investment and labor share (of value added), while there is a short-lived association with labor churning.

Overall, this section provides strong evidence that investments in digital skills are associated with increased employment, sales, and value-added at the firm level, without adversely impacting the labor share. The employment effects are broad-based, benefiting workers across various sub-categories, including women, immigrants, and university graduates. However, there is some evidence of labor churning, indicating that digitalization may lead to workforce restructuring within firms. While our distributed lag design with firm FEs and flat pre-trends is consistent with a causal interpretation, we cannot rule out that unobserved firm-specific factors simultaneously drive digital hiring intensity and employment growth. Our results should therefore be interpreted as conditional associations. To further examine potential workforce restructuring at the time of digital skill adoption, we consider the response of digitalization on employment across occupations, industries, and regions in the following subsections.

5.3. Digitalization and employment by occupation

We continue by analyzing the varied relationship between digitalization and workers across different occupations.[11] We define the outcome variable as employment in the respective occupations. Fig. 5 presents the estimates of the lead–lag models for each occupation. Overall, the results demonstrate a positive association between investment in digital skills and occupational employment across most categories. The association is strongest for managers, professionals, technicians, and clerical support workers, with peak semi-elasticities ranging from 0.6% to 1% in the years following digital skill investments.

Conversely, there is no statistically significant association between digital skill investments and the employment of service and sales workers, craft workers, plant and machine operators, and elementary occupations. None of the regressions shows a discernible pre-trend, suggesting no anticipation pattern related to digital skill investments and employment.

These findings suggest that digitalization primarily benefits employment in high-skilled occupations requiring cognitive and analytical abilities, while having a more muted impact on manual and routine

[9] Some upgrades (e.g., software licenses for existing staff) might leave no vacancy trace. Such cases likely attenuate our estimated effects towards zero; hence the positive employment responses we document are, if anything, conservative.

[10] We define labor churning as the difference between worker flows and job reallocation, see Burgess et al. (2000).

[11] The classification of occupations follows the International Classification of Occupations (ISCO).

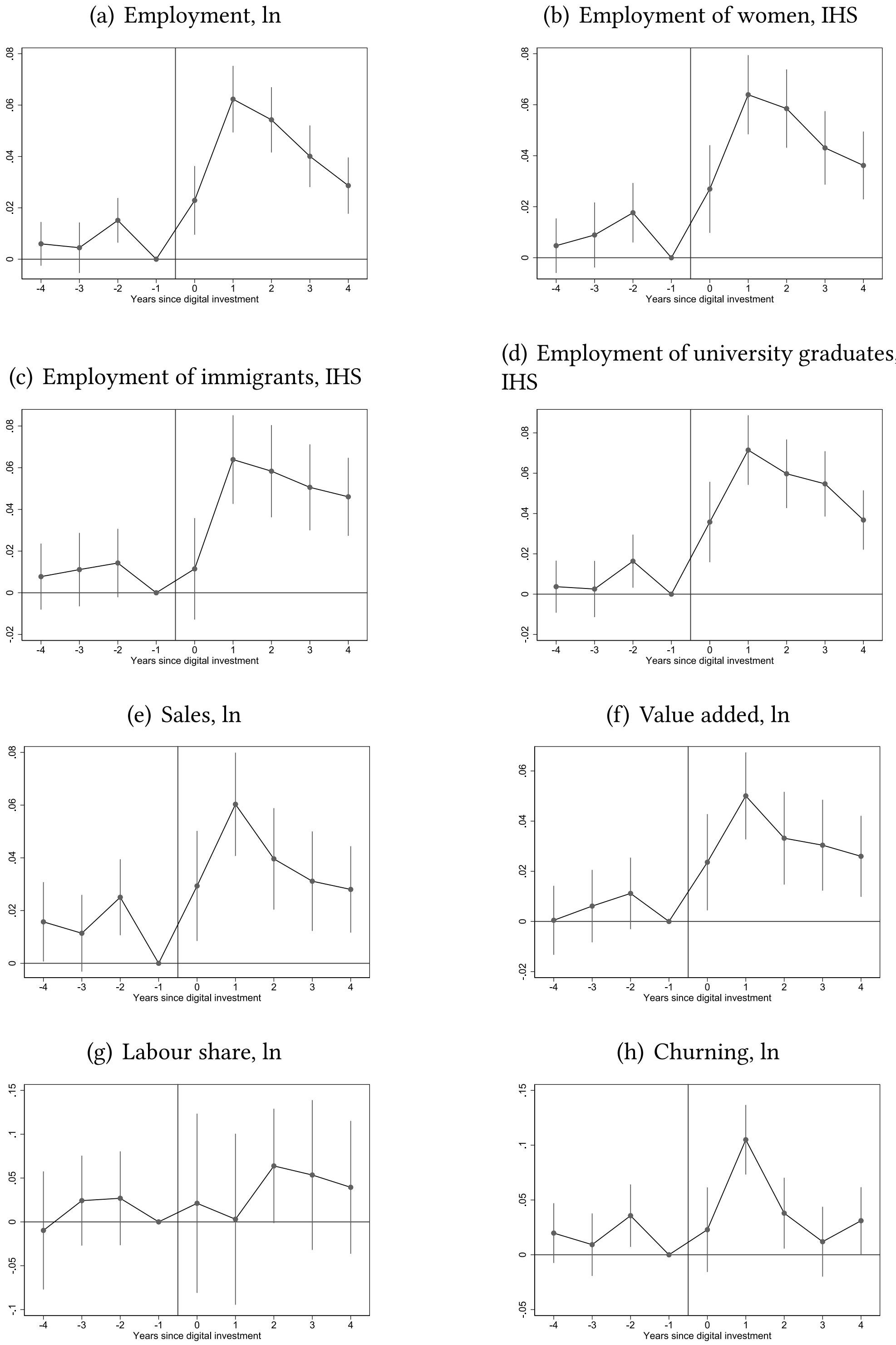

Fig. 3. Lead–lag model: Digital skill adoption.
Notes: "ln" and "IHS" refer to the natural logarithm and inverse hyperbolic sine transformation respectively. All regressions are estimated by OLS and standard errors are clustered at the firm-level. In addition to firm FEs, we control for the following set of FEs: year-by-industry-by-region (3-digit NACE, 5 regions), and year-by-the share of employees with an IT degree in 2008. We also include an indicator variable that takes on the value 1 if the firm had no job postings in a particular year. Our data include firm-year observations from 2008–2019. Sample sizes: 5349–5946 firms, 20,410–22,846 firm-year observations. 95%-confidence interval indicated.

occupations. This pattern is consistent with the notion that digital technologies complement and augment the productivity of workers in non-routine, cognitive tasks while potentially substituting for certain routine tasks.

Fig. 6 focuses specifically on the employment response to investments in data science and AI skills. In contrast to the overall digitalization measure, we find that the employment responses are concentrated in an even narrower set of occupations. Managers, professionals,

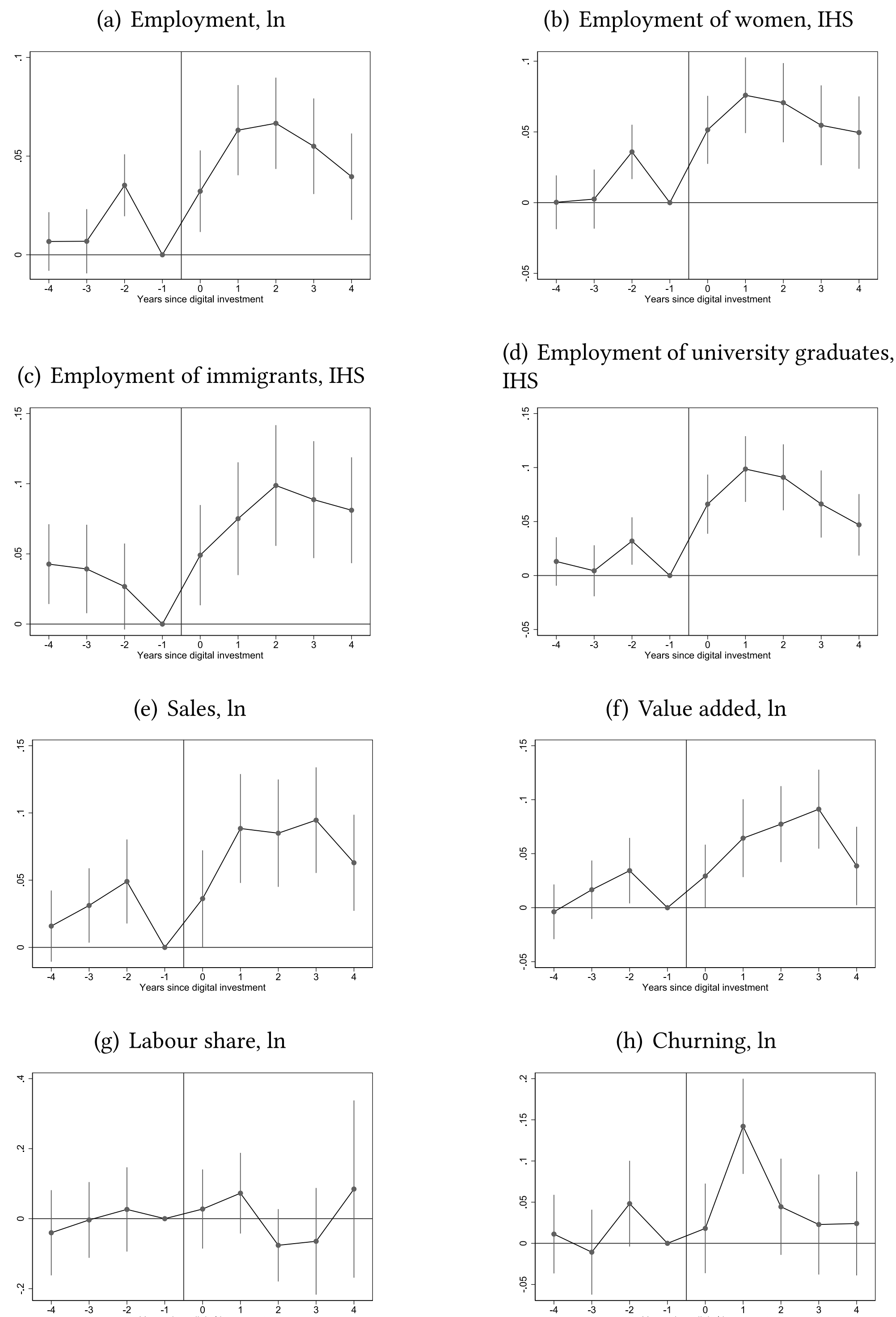

Fig. 4. Lead–lag model: Data science & AI skill adoption.
Notes: "ln" and "IHS" refer to the natural logarithm and inverse hyperbolic sine transformation respectively. All regressions are estimated by OLS and standard errors are clustered at the firm-level. In addition to firm FEs, we control for the following set of FEs: year-by-industry-by-region (3-digit NACE, 5 regions), and year-by-the share of employees with an IT degree in 2008. We also include an indicator variable that takes on the value 1 if the firm had no job postings in a particular year. Our data include firm-year observations from 2008–2019. Sample sizes: 5349–5946 firms, 20,410–22,846 firm-year observations. 95%-confidence interval indicated.

technicians, and clerical support workers benefit significantly from investments in these advanced digital skills, with peak semi-elasticities ranging from 0.8% to 1.4%. However, employment in all other occupations remains statistically unaffected by increased demand for data science and AI capabilities.

These results reveal the heterogeneous nature of the impact of digitalization across occupations, with some groups experiencing substantial increases in employment opportunities, while others do not benefit as directly. Furthermore, the findings suggest that the workforce implications of specific digital technologies, such as data science

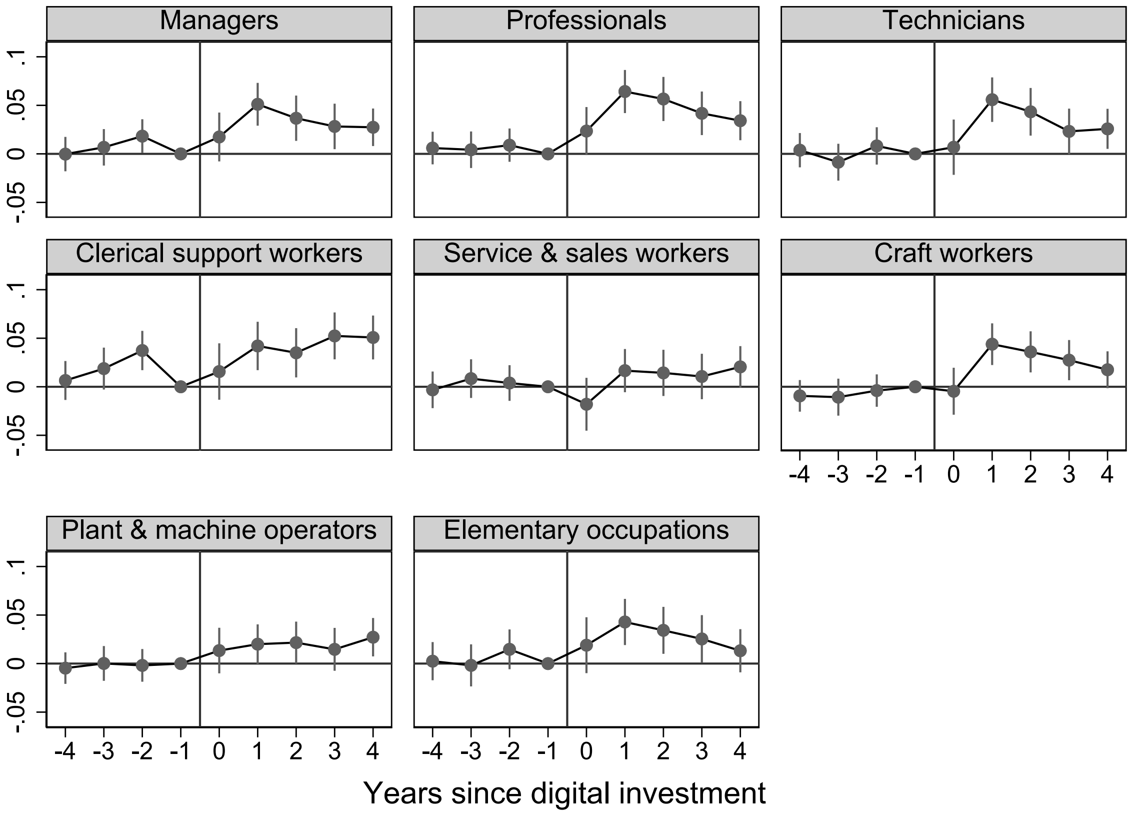

Fig. 5. Digital skills and occupational employment.
Notes: The dependent variables are the inverse hyperbolic sine transformation of firm-level employment in each occupation. All regressions are estimated by OLS and standard errors are clustered at the firm-level. In addition to firm FEs, we control for the following set of FEs: year-by-industry-by-region (3-digit NACE, 5 regions), and year-by-the share of employees with an IT degree in 2008. We also include an indicator variable that takes on the value 1 if the firm had no job postings in a particular year. Our data include firm-year observations from 2008–2019. Sample sizes: 5349–5946 firms, 20,410–22,846 firm-year observations. 95%-confidence interval indicated.

and AI, may be even more concentrated than those of broader digitalization.

The observed occupational patterns have important implications for policies aimed at facilitating digital skill acquisition and mitigating potential labor market disruptions caused by technological change. While digitalization appears to create new employment opportunities overall, the benefits are not evenly distributed across the workforce. Targeted training and education programs, as well as proactive labor market policies, may be necessary to ensure that workers in occupations facing potential displacement can transition to emerging job opportunities in the digital economy.

5.4. Digitalization and employment by industry

In what follows, we study if the patterns we observe at the firm level are heterogeneous, and test if workers in certain industries are more affected by digitalization by considering the impact of digitalization on employment by industry. Fig. 7 estimates the lead–lag models for a group of eight broad industry categories. The results reveal substantial variation in how digitalization affects employment growth across different industries.

We find that higher investment in digital skills leads to a significant increase in employment in sectors such as manufacturing, utilities, construction, trade, transportation, information and communication, finance, and professional services. The peak employment semi-elasticities in these sectors range from 0.4% to 0.8% in the years following digital skill investments by firms.

However, there are exceptions where digitalization does not appear to boost employment. The agricultural sector, education, health care, arts, and other services exhibit no statistically significant increase in employment levels when firms invest more in digital skills. For these sectors, the lead–lag estimates are centered around zero with wide confidence intervals, indicating no significant relationship between digitalization and employment.

The pattern of results points towards digitalization having a more substantial impact on employment in industries that are traditionally more trade-exposed, capital-intensive, and oriented towards the production of goods and market services. In contrast, sectors focused on local services, such as education and health care, may be less affected by digital technologies in terms of overall employment levels.

Fig. 8 presents the results for investments specifically in data science and AI skills across sectors. The findings show an even more concentrated impact compared to the overall digitalization measure. Only the ‘technical and support services’ industry shows a modest positive association between increased demand for data science and AI skills and employment, with a peak semi-elasticity of around 0.2% Employment in all other sectors does not appear to benefit significantly from higher investments in these advanced digital capabilities by firms.

The stark differences across industries and digital skill types emphasize the importance of considering the specific nature of technological change when assessing its potential labor market impacts. While digitalization may create new employment opportunities in certain sectors, the effects of emerging technologies like data science and AI could be more disruptive in other industries, potentially leading to substantial workforce reallocation.

These findings have implications for the design of industry-specific policies and initiatives aimed at supporting digital transformation and

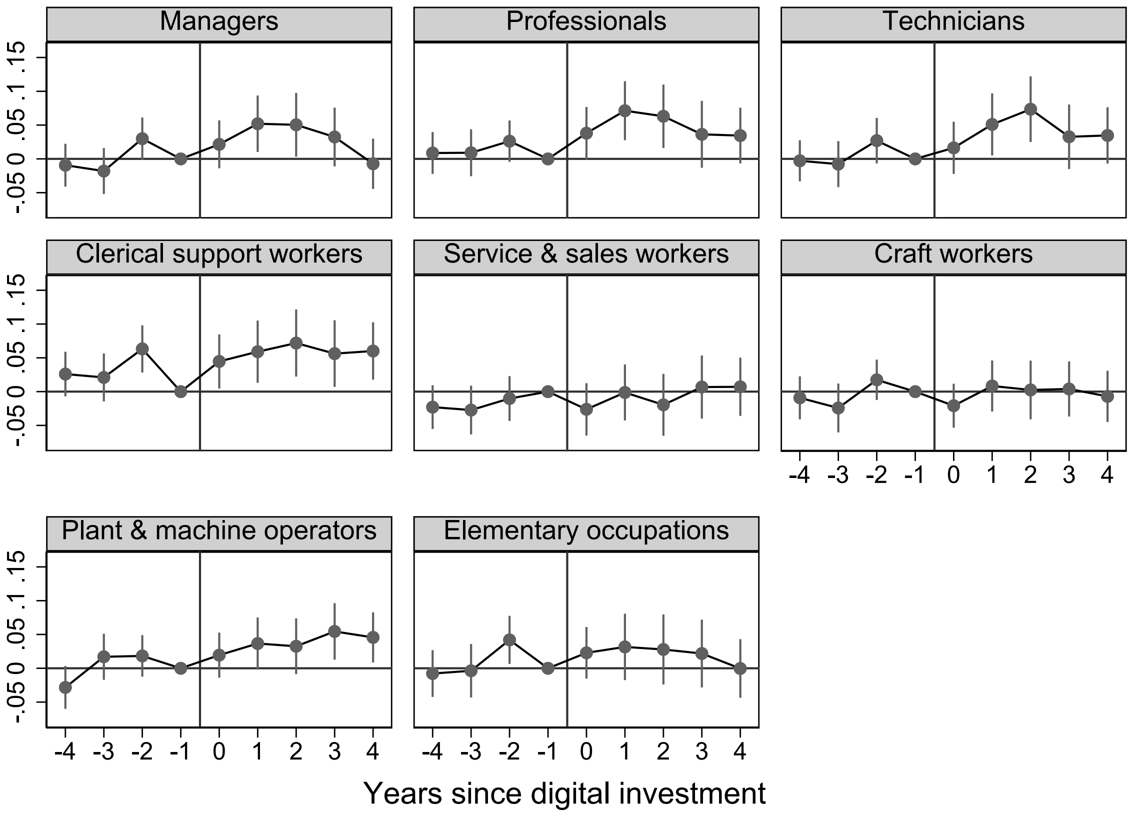

Fig. 6. Data science & AI and occupational employment.
Notes: The dependent variables are the inverse hyperbolic sine transformation of firm-level employment in each occupation. All regressions are estimated by OLS and standard errors are clustered at the firm-level. In addition to firm FEs, we control for the following set of FEs: year-by-industry-by-region (3-digit NACE, 5 regions), and year-by-the share of employees with an IT degree in 2008. We also include an indicator variable that takes on the value 1 if the firm had no job postings in a particular year. Our data include firm-year observations from 2008–2019. Sample sizes: 5349–5946 firms, 20,410–22,846 firm-year observations. 95%-confidence interval indicated.

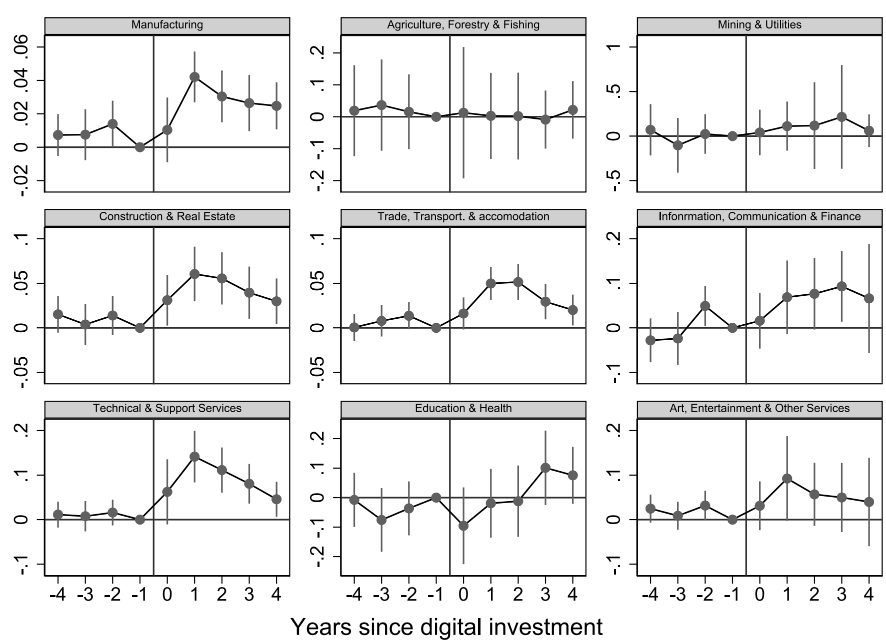

Fig. 7. Digital skills and employment by industry.
Notes: The dependent variables are the log of firm-level employment. All regressions are estimated by OLS separately for each 1-digit industry. Standard errors are clustered at the firm-level. In addition to firm FEs, we control for the following set of FEs: year-by-industry-by-region (3-digit NACE, 5 regions), and year-by-the share of employees with an IT degree in 2008. We also include an indicator variable that takes on the value 1 if the firm had no job postings in a particular year. Our data include firm-year observations from 2008–2019. Sample sizes: 5349–5946 firms, 20,410–22,846 firm-year observations. 95%-confidence interval indicated.

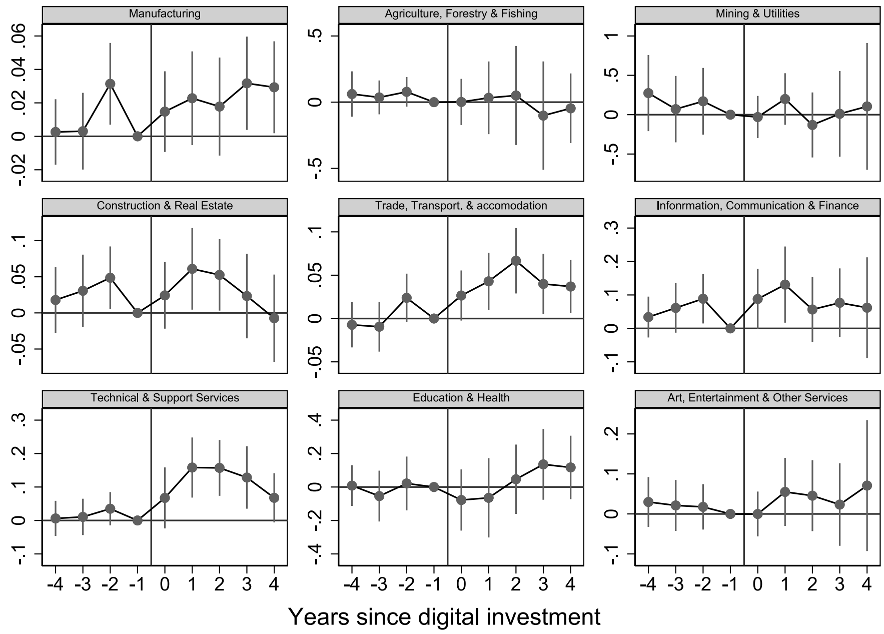

Fig. 8. Data science & AI and employment by industry.
Notes: The dependent variables are the log of firm-level employment. All regressions are estimated by OLS separately for each 1-digit industry. Standard errors are clustered at the firm-level. In addition to firm FEs, we control for the following set of FEs: year-by-industry-by-region (3-digit NACE, 5 regions), and year-by-the share of employees with an IT degree in 2008. We also include an indicator variable that takes on the value 1 if the firm had no job postings in a particular year. Our data include firm-year observations from 2008–2019. Sample sizes: 5349–5946 firms, 20,410–22,846 firm-year observations. 95%-confidence interval indicated.

fostering a skilled workforce. Industries experiencing more pronounced shifts in employment may benefit from targeted strategies for worker training, job transition assistance, and collaborations between firms, educational institutions, and policymakers to align skill development efforts with evolving industry needs.

5.5. Digitalization and employment by region

The final set of results presents the relationship between digital investment and employment across the five Danish administrative regions. As in previous sections, we present results both for the overall digitalization measure (Fig. 9) and for data science and AI (Fig. 10). The results show that employment in all regions except Northern Jutland benefits from digitalization by firms in general. The associations vary across regions, with the capital region of Copenhagen showing the highest connection to digital investments by its firms, exhibiting peak semi-elasticities of around 0.8%.

In contrast, the patterns for investment in data science and AI skills show a different regional dimension. Firms in the capital region are the only ones raising employment substantially with increasing investment in data science and AI capabilities, with a peak semi-elasticity of around 1.2%. Firms located in Southern Denmark and Central Jutland show smaller positive associations, while there is no statistically significant relationship with employment for firms located in Northern Jutland and Zealand.

This regional heterogeneity in the relationship between digitalization, data science/AI adoption, and employment may reflect differences in industry composition, skill availability, and infrastructural factors across Danish regions. The capital region, for instance, is home to a large concentration of knowledge-intensive industries and a highly educated workforce, potentially enabling firms in this region to capture greater employment benefits from investments in advanced digital technologies.

The observed regional disparities have important policy implications for ensuring balanced and inclusive digital economic development across different geographical areas. Regions that are lagging in terms of benefiting from digitalization and data science/AI adoption may require targeted support and initiatives to foster digital skill development, attract and retain talent, and incentivize firm-level investments in these technologies. Such efforts could involve collaborations between regional authorities, educational institutions, and industry partners, tailored to the specific strengths, challenges, and economic structures of each region.

Furthermore, the findings highlight the need for inter-regional coordination and knowledge-sharing to enable the dissemination of best practices and lessons learned from regions that have successfully leveraged digitalization and emerging technologies for employment growth. Such coordination could facilitate the development of coherent national strategies and policies that address regional disparities while promoting overall economic competitiveness and resilience in the face of rapid technological change.

6. Conclusion

This paper provides a comprehensive analysis of how firms' investments in digital skills shape employment dynamics in the Danish labor market. Drawing on the work of Hansen et al. (2023), we construct novel measures of digital skill demand from detailed online job posting data using BERT-models, enabling us to quantify firms' digitalization efforts over time. In line with previous findings of e.g., Czarnitzki et al. (2023) and Cardona et al. (2013), our analysis shows a robust positive link between digital investment – especially in data science and AI – and key firm productivity indicators, such as labor and total factor productivity. This correlation highlights the relevance of our digital skill metrics as indicators of technological adoption by companies.

Leveraging the longitudinal nature of our linked vacancy-employer–employee dataset, we employ dynamic distributed lead–lag models to identify the impact of digital skill investments on firm-level employment outcomes. The results provide compelling evidence that increasing demand for digital skills is associated with significant employment

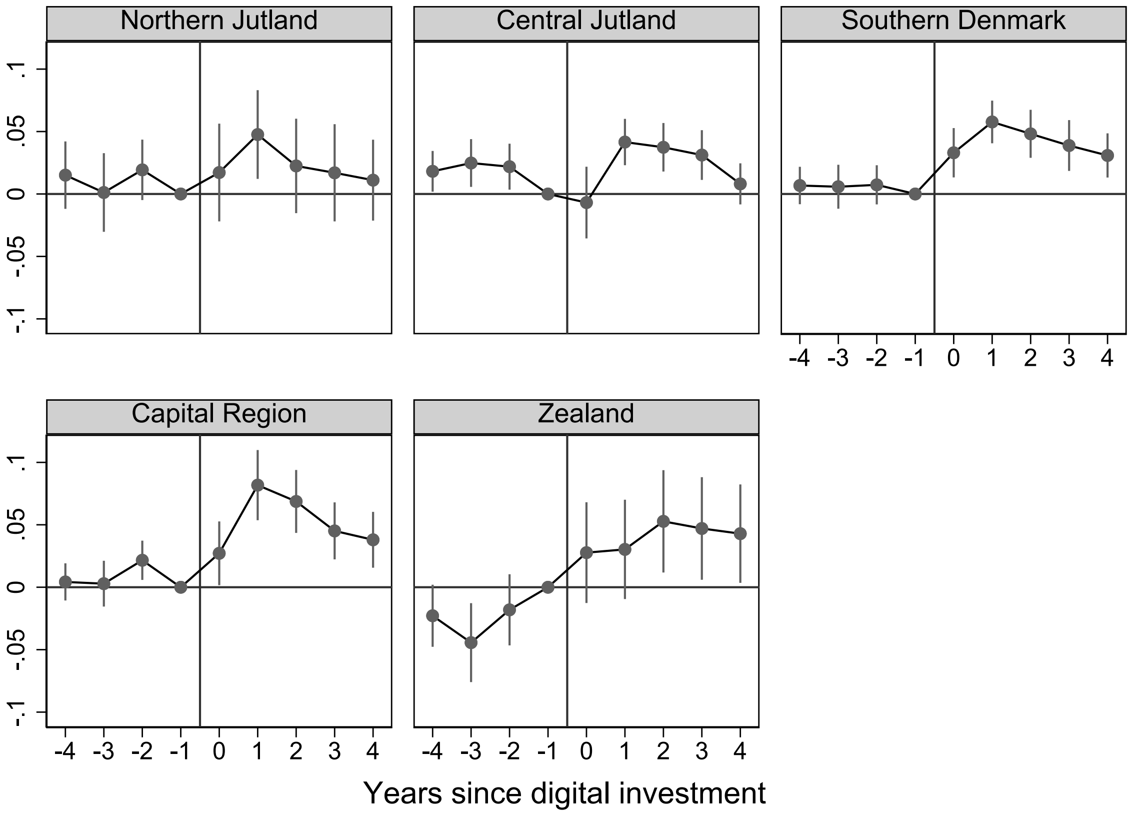

Fig. 9. Digital skills and employment by region.
Notes: The dependent variables are the log of firm-level employment. All regressions are estimated by OLS separately for each region. Standard errors are clustered at the firm-level. In addition to firm FEs, we control for the following set of FEs: year-by-industry (3-digit NACE), and year-by-the share of employees with an IT degree in 2008. We also include an indicator variable that takes on the value 1 if the firm had no job postings in a particular year. Our data include firm-year observations from 2008–2019. Sample sizes: 5349–5946 firms, 20,410–22,846 firm-year observations. 95%-confidence interval indicated.

growth within firms. Specifically, a 10 percentage point rise in the share of job postings requiring digital skills is associated with a 0.6% increase in total employment in the following year. Notably, these employment gains are broad-based, benefiting workers across skill levels, occupations, demographic groups, and most industries, challenging the notion that digitalization adversely affects employment as suggested by e.g., Brynjolfsson and McAfee (2014) or Frey and Osborne (2017). Based on the mechanisms identified in the literature review, some of the evidence presented in this paper, especially on productivity, provides empirical support for these mechanisms. In particular, the observed positive link between digital-skill investments, especially in data science and AI, and firm-level productivity aligns closely with recent findings by Calligaris et al. (2023), who highlight a positive relationship between productivity growth and employment at the firm level. This suggests that digital technologies may first raise productivity within adopting firms, which then translates into lower prices and expanded market demand. Such demand-driven expansion, as emphasized in the compensation literature (Vivarelli, 2014), likely represents an important channel through which digital investments ultimately lead to employment growth. However, our analysis also highlights heterogeneity in the impact of digitalization on labor markets. While investments in digital skills drive employment growth across multiple dimensions, the effects are most pronounced in high-skilled occupations, such as managers, professionals, technicians, and clerical support workers. Furthermore, the workforce impacts of specific digital technologies like data science and AI appear even more concentrated, primarily boosting employment in a narrow subset of occupations and industries.

Echoing the broader literature on technological change, e.g., Autor et al. (2003a), Black and Spitz-Oener (2010) and Beaudry and Lewis (2014), our findings illustrate the complex and nuanced nature of digitalization and its impacts on labor markets. Although digitalization creates new employment opportunities, the distribution of these opportunities is uneven, potentially exacerbating existing inequalities and skill mismatches in the workforce. Our results highlight the importance of targeted policies and initiatives aimed at facilitating digital skill acquisition, supporting worker transitions, and promoting inclusive economic development.

Our results also emphasize the relevance of task-based modeling framework by Acemoglu and Restrepo (2018) in which the productivity effect outweighs the displacement effect for a wide range of digital technologies, extending beyond the scope of previous empirical studies on industrial robots (Acemoglu and Restrepo, 2020) or AI (Acemoglu et al., 2022). Several limitations should be acknowledged when interpreting our findings. First, our measure of digital skill adoption is based on job vacancy text, which captures firms' demand for digitally skilled workers but may not fully reflect all dimensions of digital technology adoption, for instance, firms that retrain existing employees or that completed their digital hiring prior to our sample period are not captured. Second, while our distributed lag design with no meaningful pre-trends is consistent with a causal interpretation, we cannot definitively rule out that unobserved time-varying firm-level factors simultaneously drive both digital hiring intensity and employment growth; our results should therefore be interpreted as conditional associations rather than strictly causal effects. Third, as discussed in Section 5.1, the no-anticipation assumption underlying our design is partially limited by the planned nature of digital transformation, meaning anticipatory workforce adjustments may precede the observable vacancy signal, which would cause our estimates to represent conservative

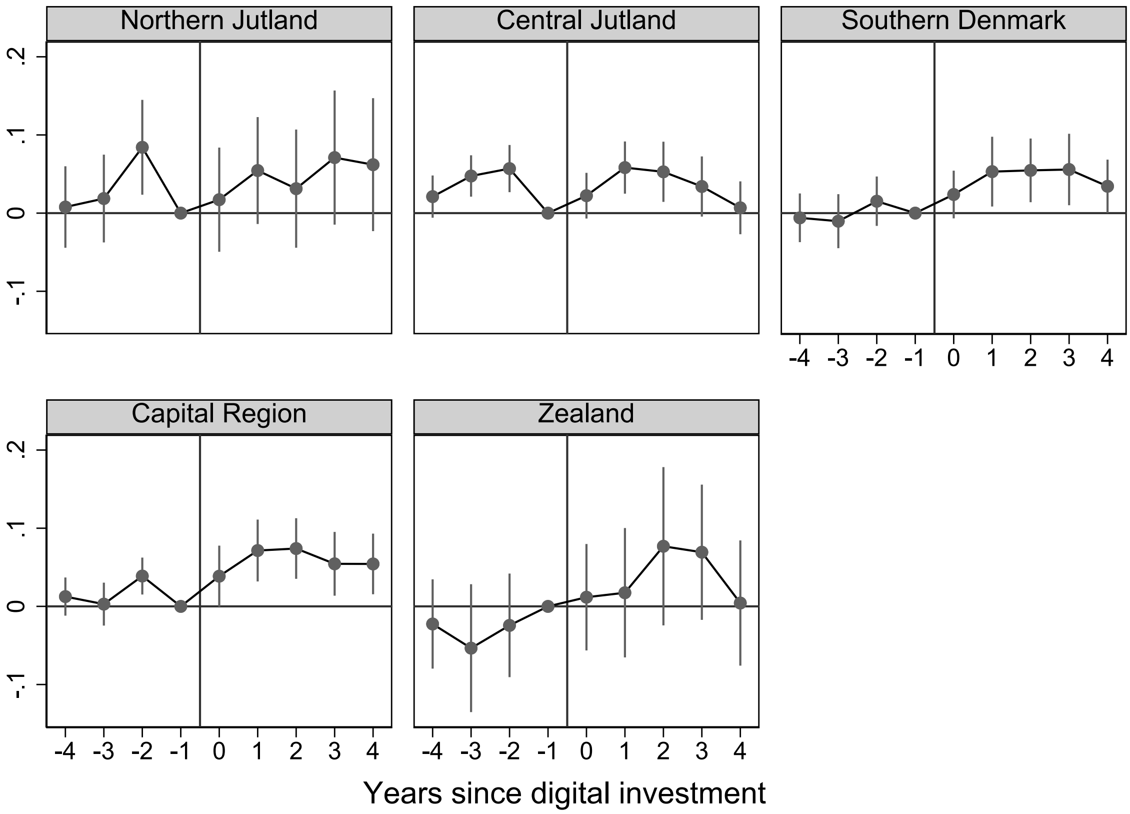

Fig. 10. Data science & AI and employment by region.
Notes: The dependent variables are the log of firm-level employment. All regressions are estimated by OLS separately for each region. Standard errors are clustered at the firm-level. In addition to firm FEs, we control for the following set of FEs: year-by-industry (3-digit NACE), and year-by-the share of employees with an IT degree in 2008. We also include an indicator variable that takes on the value 1 if the firm had no job postings in a particular year. Our data include firm-year observations from 2008–2019. Sample sizes: 5349–5946 firms, 20,410–22,846 firm-year observations. 95%-confidence interval indicated.

lower bounds (Baker et al., 2026). Finally, our data cover the period 2008–2019 and thus primarily capture pre-generative AI digitalization; the labor market implications of more recent AI technologies, such as LLMs,
may differ.

This paper contributes to the ongoing discourse on the labor market implications of digitalization and technological progress. By providing empirical evidence on the multifaceted relationships associated with digital skill investments, our findings offer essential insights for informing policy decisions and crafting effective strategies to navigate the challenges and capitalize on the opportunities presented by the rapidly evolving digital economy. Policymakers and stakeholders should prioritize industry-specific and regional strategies tailored to the unique challenges and opportunities presented by digitalization. Collaboration between firms, educational institutions, and public authorities is crucial in aligning skill development with the changing needs of industries and mitigating regional disparities that could widen with increased digitalization.

CRediT authorship contribution statement

Mathias Fjællegaard Jensen: Conceptualization, Data curation, Formal analysis, Funding acquisition, Investigation, Methodology, Project administration, Resources, Software, Supervision, Validation, Visualization, Writing – original draft, Writing – review & editing. **Cédric Schneider:** Conceptualization, Data curation, Formal analysis, Funding acquisition, Investigation, Methodology, Project administration, Resources, Software, Supervision, Validation, Visualization, Writing – original draft, Writing – review & editing.

Declaration of competing interest

The authors declare the following financial interests/personal relationships which may be considered as potential competing interests: Cedric Schneider reports financial support was provided by Rockwool Foundation Research Unit. If there are other authors, they declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Appendix A. Job postings data

To confirm the representativeness of the job postings data described in Section 3.1, we compare the share of job posts across various dimensions with the share of new job spells in the Danish administrative data. Similar to Burke et al. (2020), we find that our job postings data is largely representative of new job spells.

Fig. A.1 shows that the share of job posts is slightly higher than the fraction of new job spell in larger firms. Fig. A.2 shows that professionals are slightly overrepresented in the job posting data, and Fig. A.4 shows the same for jobs in the industrial sector. Figs. A.3 and A.5 show that these deviations remain generally stable from 2008 to 2019.

The comparisons across firm size, occupations, and industries suggest that our job postings data closely mirrors the patterns observed in administrative data on new job spells. While there are some minor deviations, the overall representativeness of the job postings data validates its use as a reliable source for analyzing digital skill demand and its impact on employment dynamics.

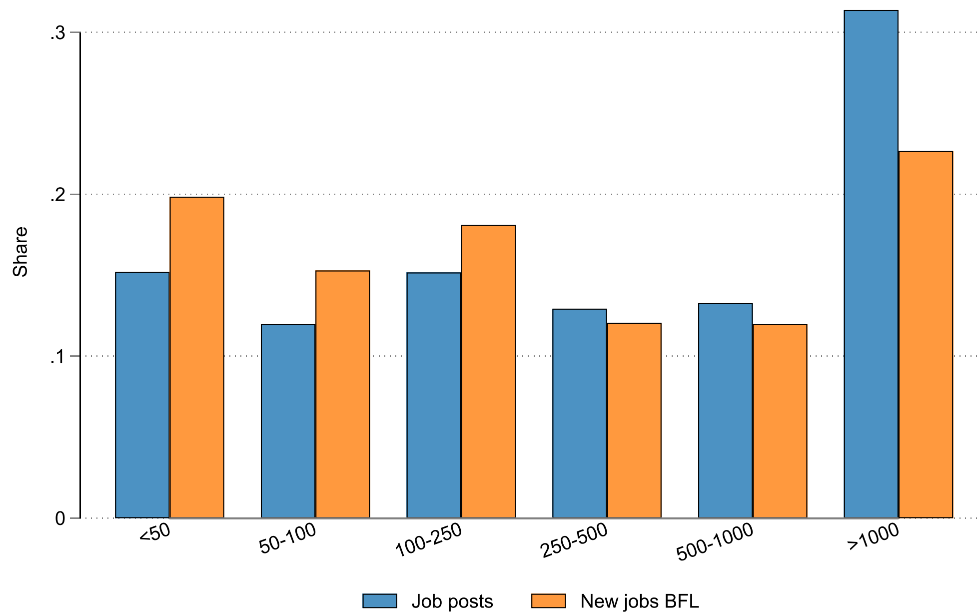

Fig. A.1. Distributions of job posts and new job spells across firm size.
Notes: This figure plots the distribution across firm size of new job spells in and job posts from private firms between 2008 and 2019, conditional on the firms posting at least one job post and a mean of 20 employees or more. Sample sizes: 449,389 job posts, 1,762,537 new job spells.

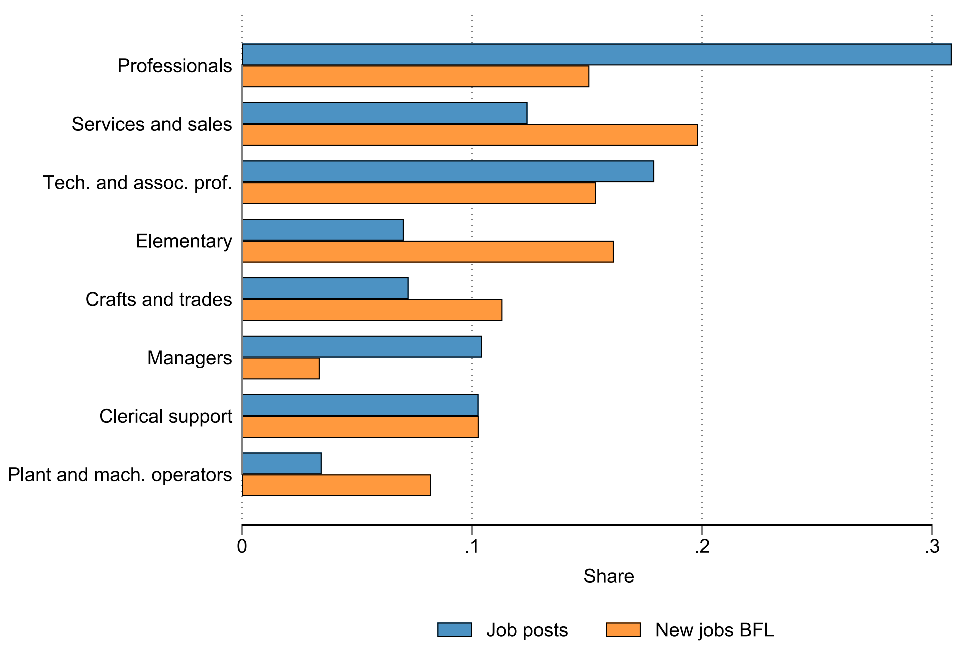

Fig. A.2. Occupational distributions of job posts and new job spells.
Notes: This figure plots the occupational distribution of new job spells in and job posts from private firms between 2008 and 2019, conditional on the firms posting at least one job post and a mean of 20 employees or more between 2008 and 2019. 1-digit ISCO08 occupations. Only occupations that account for at least 2% of either job posts or job spells are included. Sample sizes: 449,205 job posts, 1,759,802 new job spells.

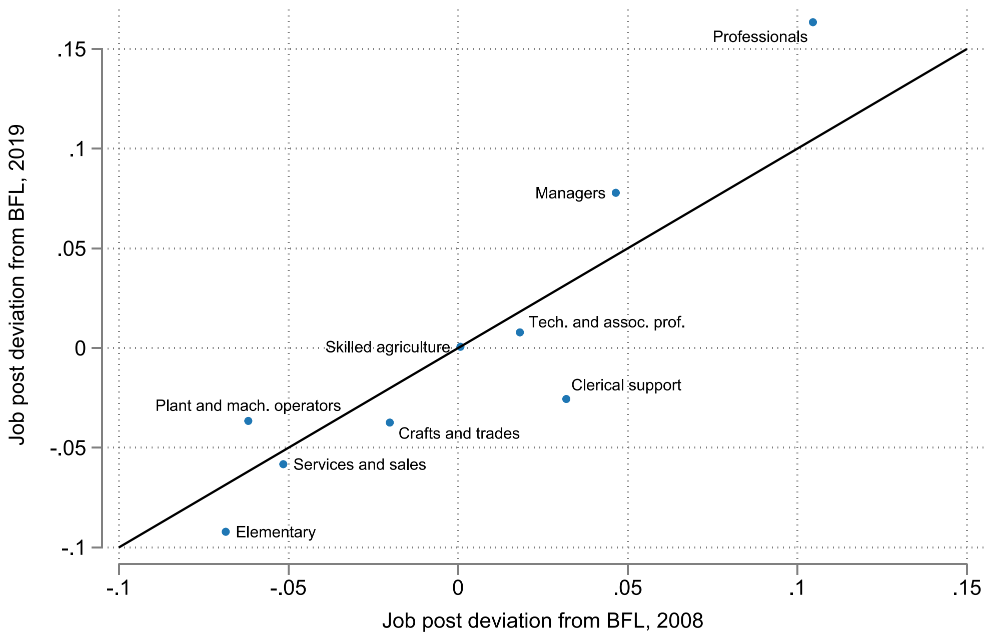

Fig. A.3. Distributional deviations, occupations, 2008 and 2019.
Notes: This figure plots the difference in occupational shares of new job spells and job posts from private firms in 2008 and 2019, conditional on the firms posting at least one job post and a mean of 20 employees or more between 2008 and 2019. 1-digit ISCO08 occupations. Sample sizes, 2008: 163,113 new job spells, 47,808 job posts; and 2019: 175,453 new job spells, 48,405 job posts.

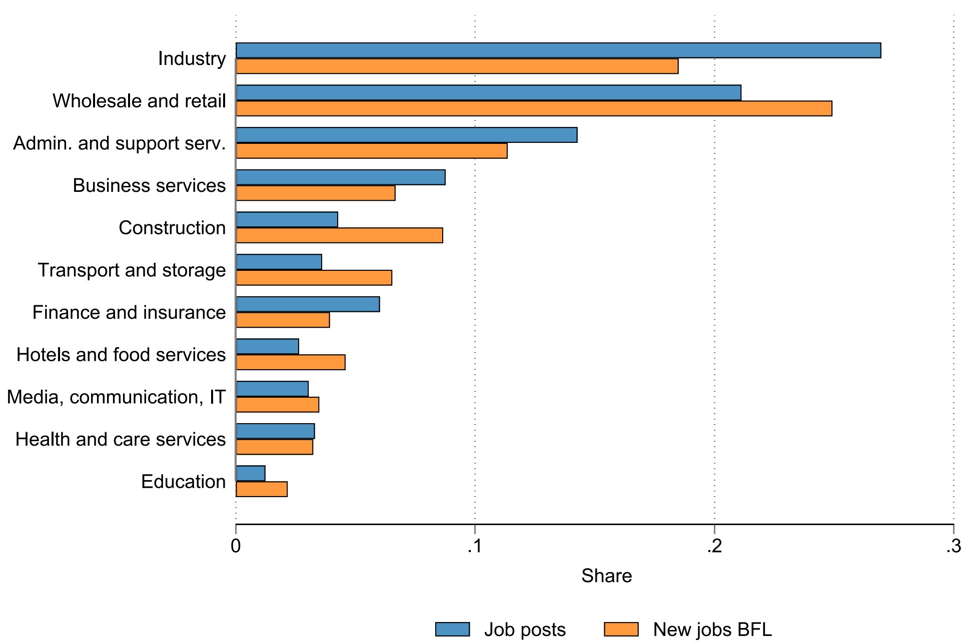

Fig. A.4. Industrial distributions of job posts and new job spells.
Notes: This figure plots the industry distribution of new job spells in and job posts from private firms between 2008 and 2019, conditional on the firms posting at least one job post and a mean of 20 employees or more between 2008 and 2019. 1-letter NACE industries. Only industries that account for at least 2% of either job posts or job spells are included. Sample sizes: 1,750,695 new job spells, 449,339 job posts.

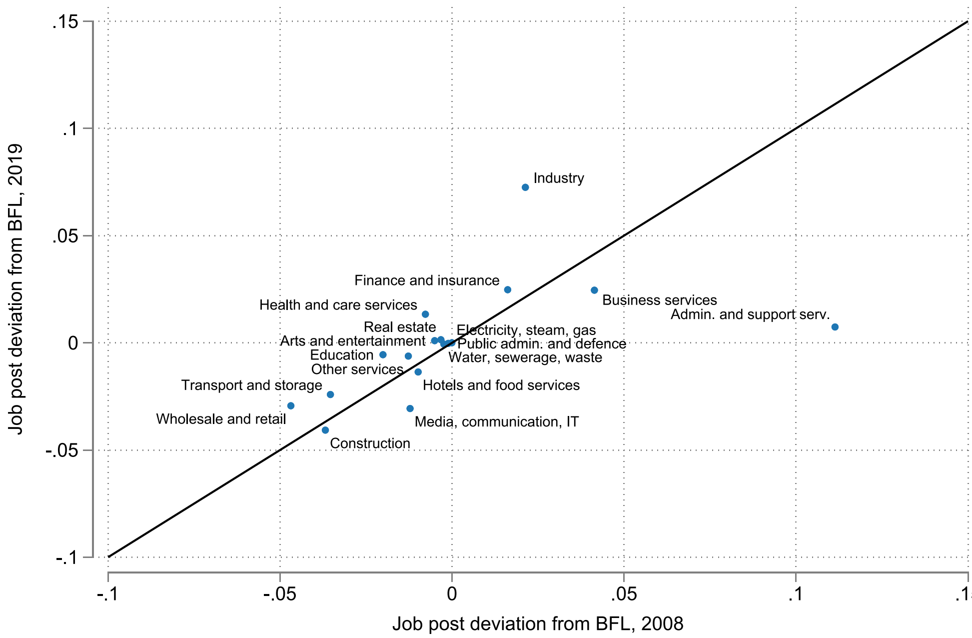

Fig. A.5. Distributional deviations, industries, 2008 and 2019.
Notes: This figure plots the difference in industrial shares of new job spells and job posts from private firms in 2008 and 2019, conditional on the firms posting at least one job post and a mean of 20 employees or more between 2008 and 2019. 1-letter NACE industries. Sample sizes, 2008: 162,322 new job spells, 47,781 job posts; and 2019: 174,808 new job spells, 48,420 job posts.

Table A.1
IT expenditure by (digital) job posting.

Type of firm	(1) IT spending as share of sales, percentile rank	(2) Fraction with IT spending above 1% of sales	(3) Firm-by-year observations
No job posts observed	44.76	0.385	2195
Job posts observed: no digital	46.91	0.398	6344
Job posts observed: incl. digital	53.64	0.503	8543

Notes: This table shows the relationship between firm-level IT expenditure and observations of job posts demanding digital skills. *"No job posts observed"* refers to the group of firms that we do not observe posting jobs across 2008–2019. *"Job posts observed: no digital"* refers to the group of firms that post jobs, but no digital jobs in the given calendar year. *"Job posts observed: incl. digital"* refers to the group of firms that post jobs, including digital jobs in the given calendar year. Column 1 reports percentile rank of total IT expenditure over total sales, ranked within calendar year. Column 2 reports the fraction of firms with IT expenditure exceeding 1% of sales. Our data include firm-year observations from 2008–2016 of firms that are observed in the survey VITU on IT expenditure.

Appendix B. Alternative specification

As mentioned in Section 5.1, the estimation of our main lag-lead models with two-way fixed effects carries an assumption of homogeneous treatment effects across cohorts. To assess the robustness of our findings against this concern, we implement an alternative estimation strategy following Bessen et al. (2025), a stacked difference-in-differences approach that explicitly relaxes the assumption of homogeneous treatment effects. Specifically, we define two separate digitalization events by identifying the first year in which firms post: (1) a number of vacancies including any digital skills that exceed 7.5% of their full-time equivalent number of employees in the same year, (2) a number of vacancies including data science & AI skills that exceed 3.25% of their full-time equivalent number of employees in the same year. These events represent major shifts in demand towards digital skills at the firm-level. As data science & AI skills are more rarely posted, we allow fraction of job post over employees to be smaller when focusing on this particular type of digital skills.

As we need four years of pre-digitalization trends in outcomes, we focus on firms that experience such digitalization events from 2012 onward. Similar to Bessen et al. (2025), we define our control group as firms that experience similar digitalization events 5 years or later after our treated firms.[12] Since our data spans from 2008 to 2019, our treatment group contain firms experiencing digitalization events in the years 2012 to 2014. Because of these restrictions, this method significantly reduces the sample size of treated firms, compared to our main strategy outlined in Section 5.1.

With our control group of future treated firms, we can estimate the following difference-in-differences model:

$$E_{ity} = \sum_{k=-4,k\neq-1}^{4} \left(\delta_k \cdot \mathbb{1}[k=t] \cdot D_i + \theta_k \cdot \mathbb{1}[k=t]\right) + \mu_i + \eta_{iy} + \lambda_{sry} + \rho_{iy} + \epsilon_{ity} \quad (6)$$

Similar to Eq. (4), E_{ity} refers to various metrics related to firm-level employment and other outcomes for firm i in year y which experience

[12] An alternative control group are firms that experience similar digitalization events *exactly* 5 years later, similar to the approach to individual-level treatment in Fadlon and Nielsen (2019, 2021). Our results are robust to using this alternative control group.

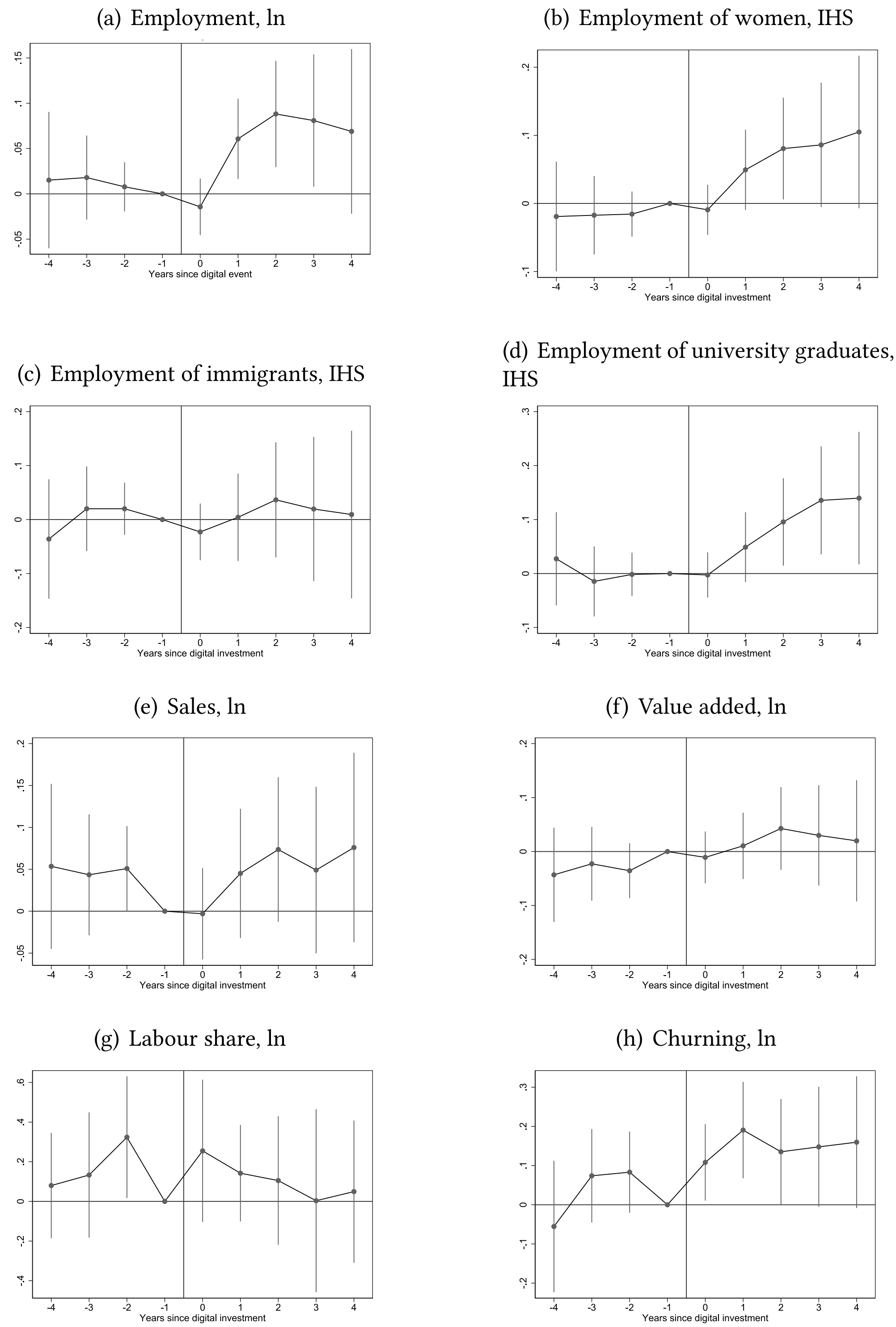

Fig. B.1. Difference-in-differences model: Digital skill adoption.
Notes: "ln" and "IHS" refer to the natural logarithm and inverse hyperbolic sine transformation respectively. All regressions are estimated by OLS and standard errors are clustered at the firm-level. In addition to firm FEs, we control for the following set of FEs: year-by-industry-by-region (3-digit NACE, 5 regions), and year-by-the share of employees with an IT degree in 2008. We also include an indicator variable that takes on the value 1 if the firm had no job postings in a particular year. Our data include firm-year observations from 2008–2019. Sample sizes: 740–802 firms, 8587–9611 firm-year observations. 95%-confidence interval indicated.

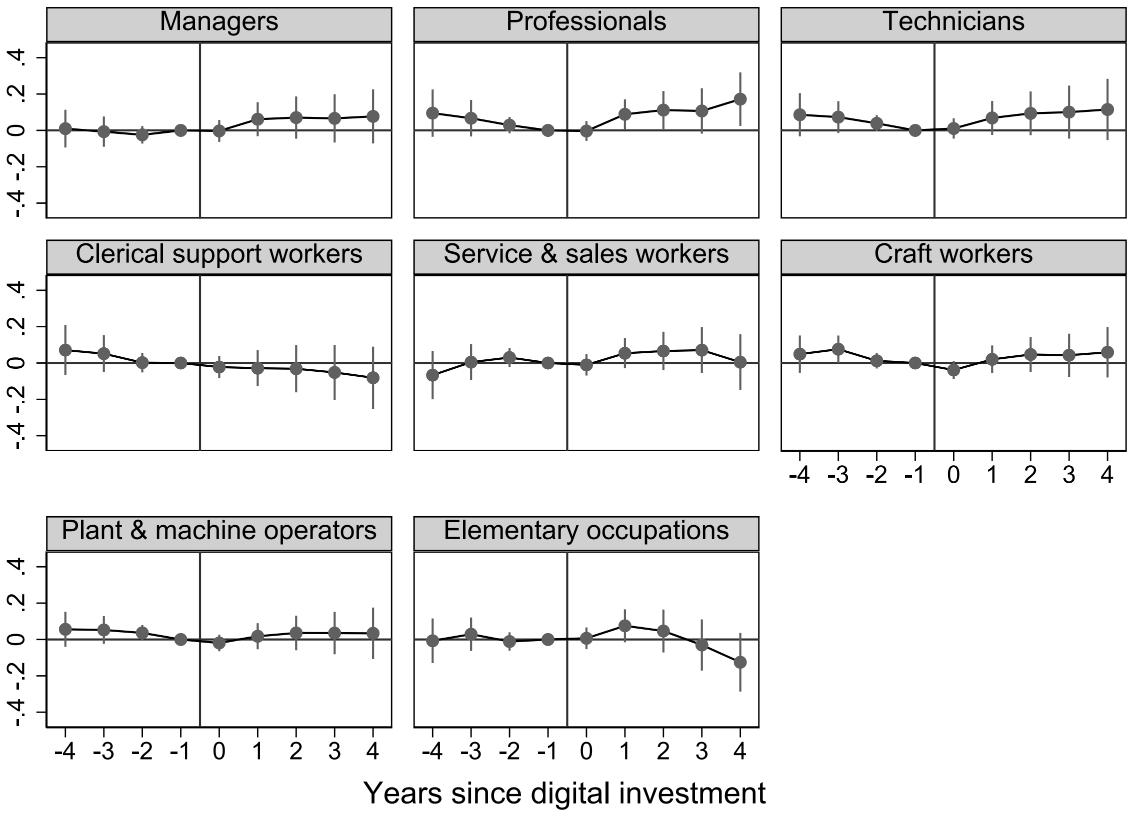

Fig. B.2. Difference-in-differences model: Digital skills and occupational employment.
Notes: The dependent variables are the inverse hyperbolic sine transformation of firm-level employment in each occupation. All regressions are estimated by OLS and standard errors are clustered at the firm-level. In addition to firm FEs, we control for the following set of FEs: year-by-industry-by-region (3-digit NACE, 5 regions), and year-by-the share of employees with an IT degree in 2008. We also include an indicator variable that takes on the value 1 if the firm had no job postings in a particular year. Our data include firm-year observations from 2008–2019. 95%-confidence interval indicated.

a digitalization event $t = -4, \ldots, 4$ years from year y. D_i is an indicator variable equal to 1 for the treated firms and 0 for their matched future-treated controls, and our parameter of interest is the vector δ_k. Control firms are assigned a pseudo treatment date from their matched treatment firm. Due to the limited time span of our data, none of the future treated control firms will enter the treatment group, so treatment status is fully captured by the firm fixed effects. Similar to Eq. (4), we include η_{iy} controlling for a trend in the baseline (in 2008) share of employment of workers with an I.T. degree, μ_i is a firm fixed effect, λ_{sry} is a year-by-industry-by-region (3-digit NACE, 5 regions) FEs, and ϵ_{ity} denotes the error term. We also add an indicator variable equal to 1 in years where firms do not post any jobs, ρ_{iy}.

B.1. Digital skills

In Figs. B.1 to B.3, we report our results from estimating Eq. (6), focusing on general digitalization events stemming from any digital skills.

In Fig. B.1, we see similar results to those from our main specification in Fig. 3. There is a noticeable increase in overall employment, alongside growing employment of women and university graduates, as well as a rise in sales and churning following digital events. However, in Fig. B.1, we do not observe increases in the employment of immigrants, value added, or in the labor share.

In Fig. B.2, we see that employment primarily increases in managerial, professional and technical occupations following digitalization events, similar to Fig. 5 using our main specification.

In Fig. B.3, we see more modest variation in effects at the regional level, and these effects are estimated more noisily compared to our main specification (Fig. 9) as our sample size is significantly reduced.

B.2. Data science and AI

In Figs. B.4 to B.6, we report our results from estimating Eq. (6), focusing on general digitalization events stemming from data science & AI skills.

In Fig. B.4, we see similar results to those from our main specification in Fig. 4. There is a noticeable increase in overall employment, alongside growing employment of women, immigrants and university graduates, as well as a rise in sales, value added, and churning following digital events. Again similar to Fig. 4, in Fig. B.4, we do not observe increases in the labor share.

In Fig. B.5, we see that employment primarily increases in managerial, professional and technical occupations following digitalization events, similar to Fig. 6 using our main specification. Unlike Figs. 6, B.5 shows increasing employment among craft workers, and no increase in employment of clerical support workers.

In Fig. B.6, we see similar variation in effects at the regional level when compared to Fig. 10, the only exception being no temporary effect of data science & AI adoption in Central Jutland.

Data availability

The data that has been used is confidential.

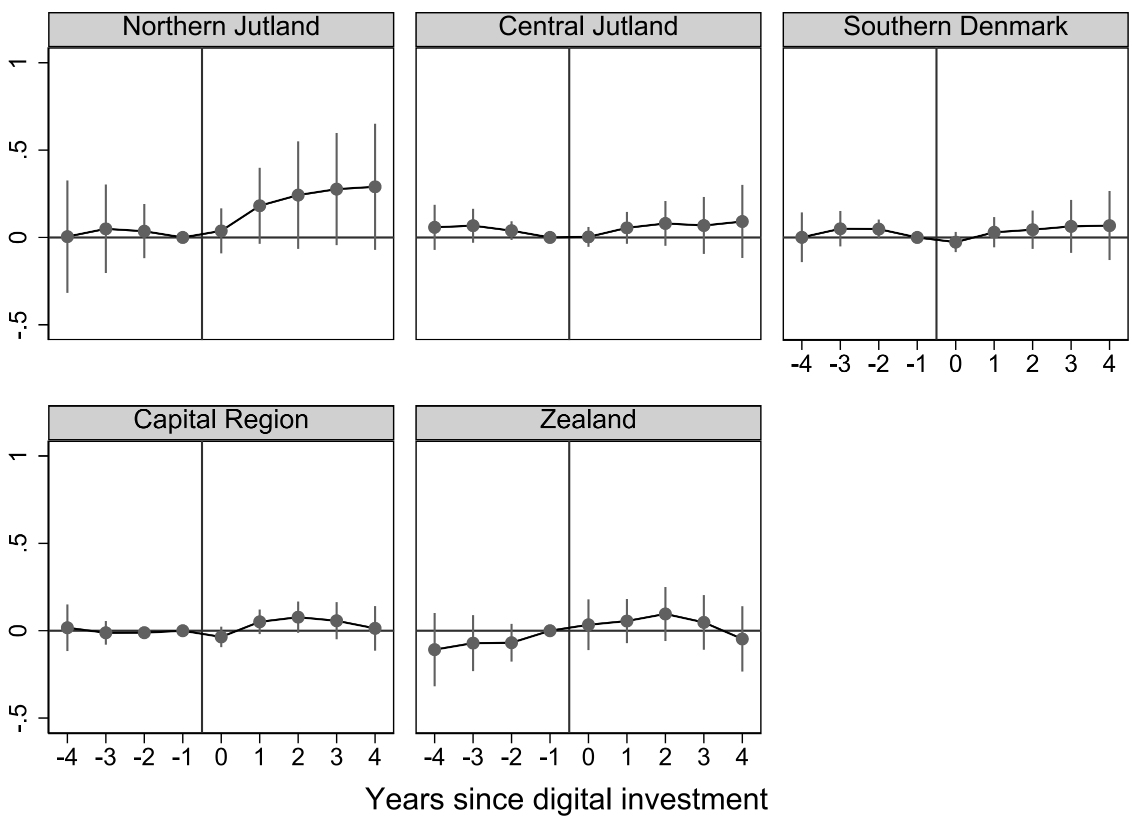

Fig. B.3. Difference-in-differences model: Digitalization and employment by region.
Notes: The dependent variables are the log of firm-level employment. All regressions are estimated by OLS separately for each region. Standard errors are clustered at the firm-level. In addition to firm FEs, we control for the following set of FEs: year-by-industry (3-digit NACE), and year-by-the share of employees with an IT degree in 2008. We also include an indicator variable that takes on the value 1 if the firm had no job postings in a particular year. Our data include firm-year observations from 2008–2019. 95%-confidence interval indicated.

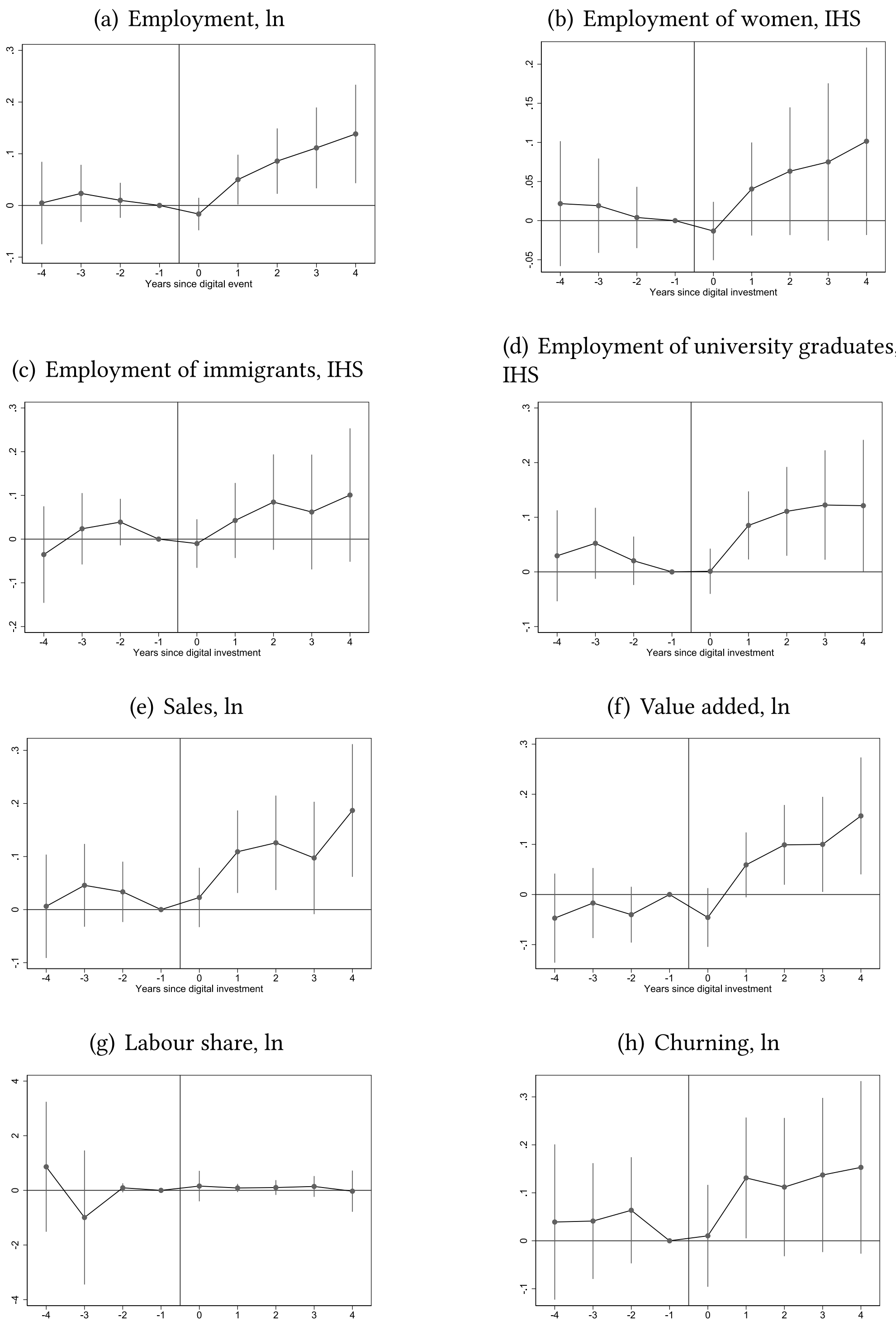

Fig. B.4. Difference-in-differences model: Data science & AI skill adoption.
Notes: "ln" and "IHS" refer to the natural logarithm and inverse hyperbolic sine transformation respectively. All regressions are estimated by OLS and standard errors are clustered at the firm-level. In addition to firm FEs, we control for the following set of FEs: year-by-industry-by-region (3-digit NACE, 5 regions), and year-by-the share of employees with an IT degree in 2008. We also include an indicator variable that takes on the value 1 if the firm had no job postings in a particular year. Our data include firm-year observations from 2008–2019. Sample sizes: 711–778 firms, 8557–9536 firm-year observations. 95%-confidence interval indicated.

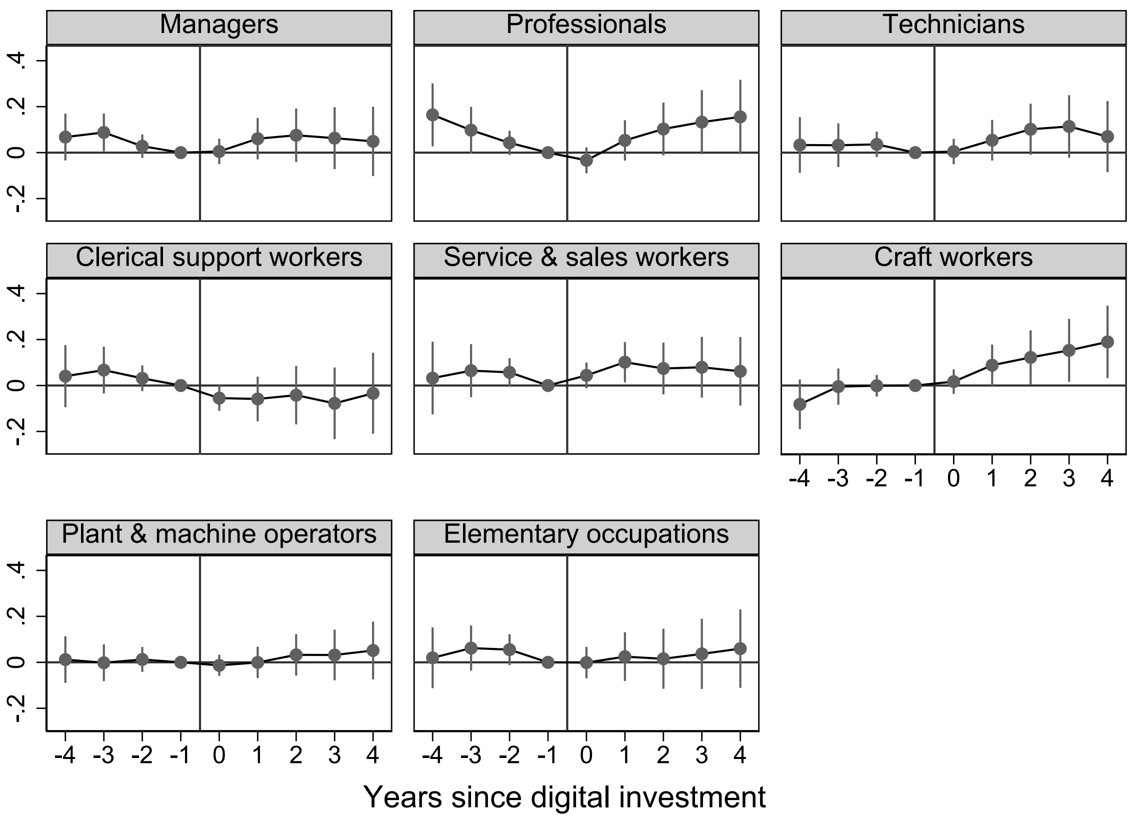

Fig. B.5. Difference-in-differences model: Data science & AI skills and occupational employment.
Notes: The dependent variables are the inverse hyperbolic sine transformation of firm-level employment in each occupation. All regressions are estimated by OLS and standard errors are clustered at the firm-level. In addition to firm FEs, we control for the following set of FEs: year-by-industry-by-region (3-digit NACE, 5 regions), and year-by-the share of employees with an IT degree in 2008. We also include an indicator variable that takes on the value 1 if the firm had no job postings in a particular year. Our data include firm-year observations from 2008–2019. 95%-confidence interval indicated.

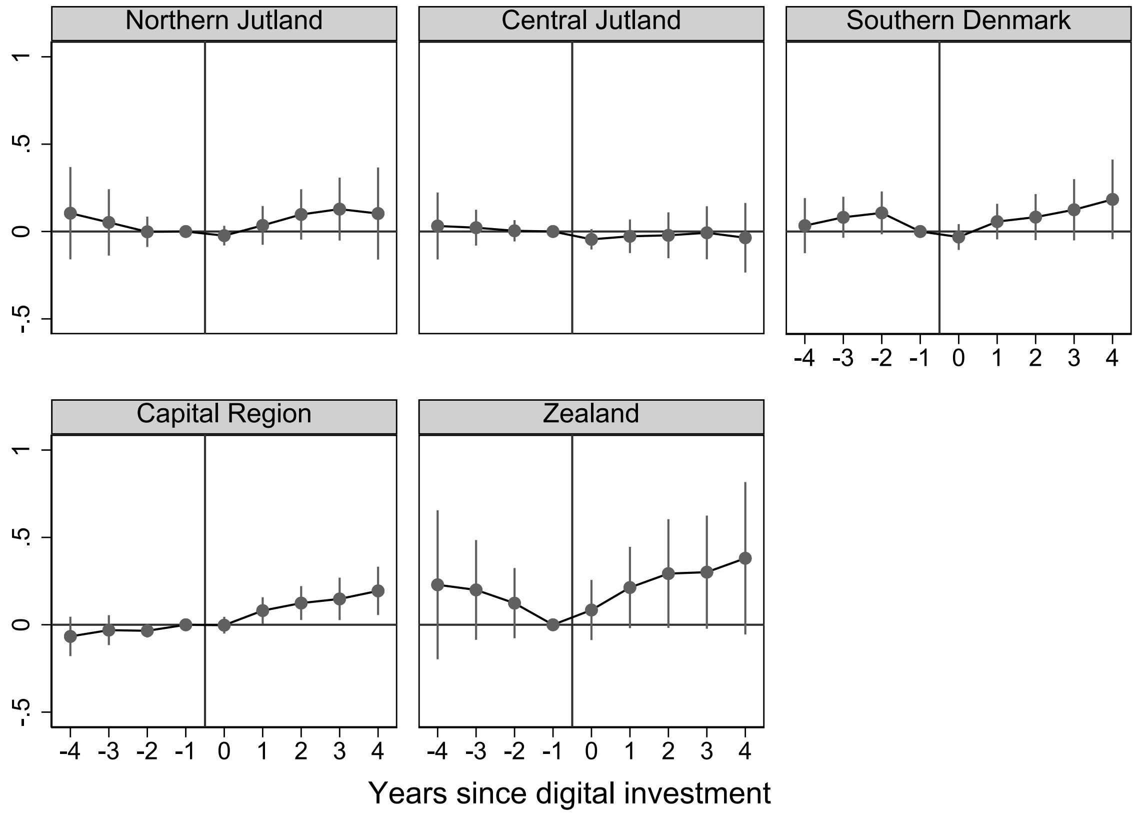

Fig. B.6. Difference-in-differences model: Data science & AI and employment by region.
Notes: The dependent variables are the log of firm-level employment. All regressions are estimated by OLS separately for each region. Standard errors are clustered at the firm-level. In addition to firm FEs, we control for the following set of FEs: year-by-industry (3-digit NACE), and year-by-the share of employees with an IT degree in 2008. We also include an indicator variable that takes on the value 1 if the firm had no job postings in a particular year. Our data include firm-year observations from 2008–2019. 95%-confidence interval indicated.

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