

# The Rise of Digital Technologies and their Impact on Demand for Labor and Skills\*

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February 2024

## Abstract

Using online job vacancy data from German firms between 2017 - 2022, we study the diffusion of digital technologies and their impact on labor and skill demand. We document a sharp increase in technological upgrading among firms since 2020, suggesting greater accessibility. To permit a causal interpretation, we exploit this COVID-induced increase in technological upgrading and perform a matched Diff-in-Diff estimation. To facilitate this analysis, we adopt a continuous treatment approach with differential treatment intensity subject to a firms' pre-COVID technology use. We show that the rebound in labor demand since 2020 was primarily driven by firms using cutting-edge technologies such as AI, suggesting adoption of novel technologies reinforces recruitment needs. These frontier firms have shifted their skill demand away from analytic and toward interactive requirements, suggesting complementarities between novel technologies and social skills. In contrast, lagging firms have raised their demand for analytic skills at the expense of interactive skills —underscoring widespread upskilling in job requirements. Our results reveal previously unexplored heterogeneities in labor and skill demand between firms, which could possibly exacerbate ongoing labor shortages.

**Keywords:** Job Vacancies, Labor Demand, Skill Demand, Digital Technologies

**JEL Codes:** D22, J23, J24, J63, O33

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\*We are grateful to Eduard Brüll, João Pereira dos Santos, Lukas Hoernig and Sandra Schaffner for sharing code, data, and valuable insights. We also thank Anastasia Suckau for excellent research assistance. All remaining errors are our own.

# 1 Introduction

Over the last decade, we have witnessed rising adoption of new, cutting-edge digital technologies (DT), such as AI (ZEW 2022, Schaller et al. 2023), Cloud Technologies (DeStefano, Kneller & Timmis 2023), and 3D-printing (Ben-Ner et al. 2022). These technologies are self-controlled and fully integrated in firms' (already existing) IT-infrastructure. While some firms at the technological frontier adopt these new technologies ("frontier firms"), most firms have not yet entered this stage (Genz, Gregory, Janser, Lehmer & Matthes 2021) and are thus lagging behind. More recently, it has been shown that this digital transformation has been accelerated by the COVID-19 pandemic, or "Pandemic Push" (Gathmann, Kagerl, Pohlen & Roth 2023), as a substantial share of firms invested in new technologies, solely because of the COVID-induced circumstances (see also Barth, Bryson & Dale-Olsen (2022)). These DT investments appear to be long-lasting and thus have major implications for the future of work, most of which are still unknown.

This emerging literature has identified early and important insights on the ramifications of firm-level adoption of digital technologies, such as for training, resilience, employment, and wages (Genz et al. 2021, Gathmann et al. 2023), institutional adjustments (Barth, Bryson & Dale-Olsen 2022), and rising digital divide between firms, i.e. unequal access to DTs (Arntz, Genz, Gregory, Lehmer & Zierahn-Weilage 2024). Existing studies primarily use firm-level survey data on technology adoption, which offers rich information for special circumstances. However, these data lack depth for more complex implications, such as specific type of technology adoption or changing skill requirements. These are important channels as new technologies usually display complementarities with skilled labor (Krusell, Ohanian, Rios-Rull & Violante 2000a). Yet, this relationship also depends on the type of technology employed, with ambiguous implications for labor and skill demand (Kogan, Papanikolaou, Schmidt & Seegmiller 2023). Improving our understanding on these channels is imperative from a policy-perspective as many firms are currently struggling to compete for talent in an environment characterized by rising digitalization and labor shortages.

A key challenge to explore these mechanisms in more detail is data availability. New technologies are, by definition, recent. To study not only their adoption, but also their dynamic implications, requires preferably longitudinal data with near real-time features. In this paper we fill this gap, using up-to-date online job vacancy data from 2017 - 2022. We propose a simple, yet effective method to identify and classify key technologies in vacancies and use them to explore our research questions on the recent surge in digitalization:

- 1) How do digital technologies diffuse among firms? Is the digital divide between frontier

and lagging firms currently increasing or decreasing?

2) How do firms adjust labor and skill demand when they face a sharp increase in digitalization?

To answer these questions, we use monthly online job vacancy (OJV) data from German firms, spanning 2017m1 - 2022m12, comprising a panel of posting firms. Our data gives us novel access to the raw text data, allowing us to infer firms' use of digital technologies directly from vacancy descriptions and study their implications for labor and skill demand.<sup>1</sup> We measure labor demand using firms' job postings and skill demand using task requirements from the job profile (note we use 'skills' and 'tasks' interchangeably throughout).

Germany offers an interesting setting for our research questions. On the one hand, many German firms are considered technology leaders in their respective field —either as large international corporations (e.g., ALDI, Siemens, Volkswagen) or mid-sized "Hidden Champions" (Venohr & Meyer 2007), who are global leaders in highly specialized areas. On the other hand, though, Germany has repeatedly been identified as a "digital laggard" compared to other OECD countries, given its rather slow diffusion of digital technologies (EFI 2022). Therefore, the German setting offers rich heterogeneity in firms' technology levels to study the questions of interest in this paper.

In the first part of the paper, we answer our first research question by exploring the diffusion of distinct technology classes over time and exploring a possible digital divide between German firms. We loosely follow Genz, Gregory, Janser, Lehmer & Matthes (2021) and distinguish between two classes of technologies: 4.0 technologies and 3.0 technologies. 4.0 technologies comprise new cutting-edge digital technologies (e.g., AI, Cloud Technologies, VR) that have started to become mainstream only since the 2010s (ZEW 2022). In contrast, 3.0 technologies comprise technologies from the third industrial revolution, starting ca. late 1970s (e.g. MS-Office Tools, CNC, many programming languages). Subsequently, we assign firms into three distinct technologies tiers subject to their use of these technologies. Specifically, we distinguish between "4.0 firms" for which we find references to 4.0 technologies in their postings. Similarly, we define "3.0 firms" as those with references to 3.0 technologies —but no 4.0 technologies —and "2.0 firms" as those with references to neither technology group. For this reason, we interpret these 2.0 firms as "lagging firms" in terms of technology use.

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<sup>1</sup>This data has been scraped by our partner, a private IT company, covering the near-universe of job postings and spanning January 2017 until December 2022. We are continuously receiving new batches of data. To date, we have data until June 2023, which we are currently preprocessing. A novel aspect of this data is that we have access to the original text data, allowing us to develop our own transparent taxonomy for task data and having complete control over the data-generating process.

Our first main finding is a sharp drop in the share of 2.0 firms over time. In 2017, more than 30% of firms in our sample were classified a 2.0 firm. By the end of 2022, this fraction dropped to about 10%. At the same time, we observe a steady increase in the share of 4.0 firms, from about 15% to 25%, and 3.0 firms, from about 55% to 65%. We interpret switches from one technology tier to a (higher) one as technological upgrading within a firm. Following this intuition, our results do not conform with a digital divide, as suggested by previous research using survey information on technology investments (Gathmann, Kagerl, Pohlan & Roth 2023, Arntz, Genz, Gregory, Lehmer & Zierahn-Weilage 2024). Instead, our results suggest a broad diffusion of digital technologies among German firms since at least 2017. To shed more light on these dynamics, we continue analyzing the timing of these transitions. To this end, we identify the first time a firm provides references to technologies from more advanced technology tiers. For example, we find that in any given month about 6% of 2.0 firms have become 3.0 firms pre-pandemic (i.e. technological upgrading). Since 2020, however, this share has increased to 7.5%, implying a 25% increase in the pace of technology upgrading within the group of 2.0 firms.<sup>2</sup> Similarly, albeit weaker in magnitude, we find that around 2.5% of 3.0 firms have become 4.0 firms in any given month pre-pandemic and 3% afterwards. Overall, our analysis reveals a sharp increase in technological upgrading among firms, consistent with the Pandemic-Push-Phenomenon.<sup>3</sup>

In the second part of the paper, we turn to the implications of rising digitalization by studying firms’ adjustments in labor and skill demand. To permit causal interpretation, we perform a matched Diff-in-Diff estimation at the firm-level in which we exploit the COVID-induced rise in technological upgrading for exogenous variation. A key challenge is that standard binary treatment settings are not applicable because all firms were treated by the pandemic (thus there is no natural control group).

To overcome this challenge, we apply a continuous treatment research design, building upon recent advances in the econometric literature (Callaway, Goodman-Bacon & Sant’Anna 2021, de Chaisemartin, d’Haultfoeuille, Pasquier & Vazquez-Bare 2022). Our empirical ap-

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<sup>2</sup>Note that we permit firm entry in our sample, i.e. firms are also included in our analysis even if they had not posted any vacancies in the baseline year 2017. While this introduces some compositional changes, a perfectly balanced sample (i.e. containing only firms who posted throughout our time horizon) mechanically reduces the share of 2.0 firms. The reason is that any 2.0 firm that becomes a 3.0 firm could not be replaced by another 2.0 firm that only recently started posting vacancies. This restriction would severely compromise our analysis on the timing of potential technology adoption. Instead, we provide remedy by limiting our sample to firms which have posted vacancies at least two years pre- and post-pandemic. This restriction removes firms which only posted vacancies before or after 2020, but in both periods.

<sup>3</sup>Interestingly, this upgrading is most pronounced among the previously least digital firms, implying that these firms increasingly use technologies that have been around for many decades. This pattern is consistent with technology investments solely because of the COVID-induced disruption in working places, documented in survey-based evidence (Gathmann, Kagerl, Pohlan & Roth 2023, Barth, Bryson & Dale-Olsen 2022).

proach assumes that some firms were treated more intensely by the pandemic push than others. But which ones? In our setup, we assume 2.0 firms to be the primary treated group. We justify this choice on two grounds. First, our descriptive evidence from the first of the paper suggests stronger technological upgrading among 2.0 firms, which is indicative of higher treatment intensity. Second, most technologies that have gained momentum since the pandemic already existed well beforehand (e.g., videoconferencing, collaborative technologies). Despite that, 2.0 firms had little experience with these technologies (based on vacancy descriptions). The COVID-induced disruptions, however, forced many firms of these firms to adopt digital technologies to keep their businesses running (see e.g., [Barrero, Bloom & Davis \(2023\)](#)). To account for non-random selection into technology tiers, we supplement a two-stage matching procedure in which we combine exact matching within the same 1-digit industry with coarsened and propensity score matching.<sup>4</sup>

Our second main finding is that firms’ adjustments in labor and skill demand since the Pandemic Push displays substantial heterogeneities, depending on their (assigned) technology tier. We find that all firms raised their labor demand. Yet, digitally more advanced 3.0 and 4.0 firms have experienced a stronger shift in labor demand, by about 0.6 postings per month (accounting for size differences). We also find substantial shifts in skill demand since 2020. For example, 2.0 firms have raised their skill requirements in the pandemic push era, especially pertaining to routine cognitive tasks, by about 2 pp. To put this result into perspective, keep in mind the pre-pandemic average for 2.0 firms was 0.19 (implying that 19% of all demanded job tasks were routine cognitive). Our finding thus implies a nearly 10% increase in demand for routine cognitive skills —primarily at the expense of manual tasks (-1.6 pp., - 5% relative to pre-pandemic average).

In a robustness exercise, we re-define our treatment, this time imposing higher treatment intensity on 2.0 *and* 3.0 firms. This analysis further reveals strong shifts in skill demand among abstract activities. Combined, 2.0/3.0 firms have increased their demand for analytic tasks by 5.5 pp., relative to 4.0 firms (i.e., the updated control group). Considering the pre-pandemic average of 0.29, our findings imply a sizeable increase in relative demand for abstract tasks on the order of 19%. Instead, 4.0 firms have increased their demand for interactive tasks —compared to 2.0/3.0 firms by 3.3 pp. (12% rel. to pre-pandemic avg.). While speculative at the moment, our results are consistent with complementarities between 4.0 technologies, such as AI, and interactive skills. Overall, our findings indicate widespread upskilling among firms, yet, different coping mechanisms that may give rise to between-firm heterogeneity in skill demand.

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<sup>4</sup>Our matching procedure draws upon established methodologies in the literature, e.g. [Blien, Dauth & Roth \(2021\)](#), [Arntz, Ivanov & Pohlman \(2022\)](#), [Hethy-Maier & Schmieder \(2013\)](#).

Our paper makes several contributes to the literature. First, our study contributes to the emerging literature on the diffusion of digital technologies. Several studies have shown with firm-level surveys that adoption of technologies such as AI, Cloud, and others has been on the rise across many countries.<sup>5</sup> These studies provide important snapshots on differential use of technologies. Yet, they lack variation over time and depth to distinguish distinct technologies. While we do not observe actual technology adoption, our rich job descriptions allow us to infer technology upgrading based on repeated information on technology use at work. We thus interpret our technology measures as *potential* technology adoption. Observing firms’ job posting descriptions over time further allows us to study dynamics, such as shifts from one technology tier to another. Using our OJV data and classification methods, we are also able to replicate (i) well-known stylized facts, such as regional and industry-specific concentration of certain technologies, and (ii) a representative distribution of firms across distinct technology tiers (“2.0”, “3.0”, “4.0”). Our approach thus offers an alternative path to study diffusion of technologies, compared to the existing survey-dominated literature.

Second, and closely related, we contribute to the nascent literature that explores contemporaneous technology adoption since the pandemic (Barth, Bryson & Dale-Olsen 2022, Gathmann, Kagerl, Pohlen & Roth 2023). Using insights from linked survey and administrative data, these papers study implications for training, resilience, employment, and wages. Their findings suggest that recent investments into digital technologies have contributed to a rise in digitalization (“Pandemic Push”) —however with unclear consequences for work processes. We shed new light on these consequences, showing heterogenous responses in firms’ labor and skill demand subject to their pre-COVID experience with digital technologies. In general, we find rising skill requirements across all firm types. On top of that, we also provide evidence for previously unexplored channels, such that firms with more advanced technologies (“4.0”) concurrently raise their demand for interactive tasks with greater intensity. These observations add a more nuanced perspective to the reported “digital divide” (Gathmann, Kagerl, Pohlen & Roth 2023), which is based on firm-specific investment behaviour.

Third, and more broadly, we also contribute to the literature on the “Future of Work”. These studies often study innovations in the workplace, such as the shift to remote work and rising prevalence of collaborative technologies.<sup>6</sup> Our detailed data allows us to track the emergence of these, but also many other technologies. We thus offer broader insights on changing work processes that result from digitalization.

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<sup>5</sup>See, e.g., for Germany (Genz, Gregory, Janser, Lehmer & Matthes 2021, Rammer 2022), US (Acemoglu, Anderson, Beede, Buffington, Childress, Dinlersoz, Foster & Goldschlag 2022, Bloom, Hassan, Kalyani, Lerner & Tahoun 2021), or Norway (Barth, Bryson & Dale-Olsen 2022).

<sup>6</sup>See, e.g., Alipour, Falck & Schüller (2023), Alipour, Langer & O’Kane (2021), Dingel & Neiman (2020), Barrero, Bloom & Davis (2020, 2021), Adams-Prassl, Boneva, Golin & Rauh (2022).

Fourth, we contribute to the literature on Recessions & Recruiting. Many studies have shown how recessions lead to temporary collapses in labor demand, e.g. during COVID<sup>7</sup>, but permanent increase in skill requirements (Hershbein & Kahn 2018, Modestino, Shoag & Ballance 2019). We use insights from this literature, and extend them by highlighting the importance of firm heterogeneities in technology use. More generally, we make a methodological contribution to this literature. Most of these studies offer descriptive evidence since business cycle shocks affect all firms. Finding suitable treatment and control groups for causal inference has thus been a challenge. We overcome this challenge by combining a matching procedure with new causal methods that allow for differential treatment intensity.

## 2 Data

### 2.1 Online Job Vacancies

#### 2.1.1 Data-Generating Process

We use a unique data source consisting of the near-universe of online job vacancies posted in Germany between January 2017 and December 2022. The job postings are collected by our private partner, a firm that is offering custom-made firm-, person- and job posting-data and market analysis. Our partner scrapes more than 2,000 web-pages for vacancies from the following platforms: (i) job boards (fee paying), (ii) job boards (free of charge), (iii) company websites, (iv) temporary employment agencies, and (v) head-hunters. They consistently update their online sources and scrape all sources on a daily basis. Subsequently, our partner performs some basic cleaning procedures, such as removal of “boilerplates” (i.e., content that is unrelated to the vacancy, such as ad text) and removes duplicates from the same source (i.e. sources from the same url address). A unique feature of this data is that our partner merges posting firms with the German company registry (“Handelsregister”). This merge is successful for about 60% of firms.<sup>8</sup> Subsequently, our partner sends us the data, outlined below.

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<sup>7</sup>See, e.g., Bamieh & Ziegler (2020), Campello, Kankanhalli & Muthukrishnan (2020), Forsythe, Kahn, Lange & Wiczer (2020a,b), Hensvik, Le Barbanchon & Rathelot (2021), Blanas & Oikonomou (2022).

<sup>8</sup>The data set is based on information from the Handelsregister and includes all firms that are listed in the Handelsregister since 1991. About half of the 3,4 Mio. firms in Germany are noncommercial and therefore not listed in the Handelsregister. In addition, firms from the public administration sector are not included. The firm level data includes information about the firm name, the complete address, legal status, industry, original stock and business volume, the number of employees and the formation date. The data can be merged through a firm identifier, which is available for about 60% of the job postings. Reasons why the firm identifier is not available are, on the one hand, that firms are not listed in the Handelsregister, or, on the other hand, because group of companies cannot be assigned to one specific firm.



One, we receive firm information, containing the location of the firm (in many cases at zip-code level), industry, and other important background information. Two, we receive person information, such as sex, function, and date of birth of the owner. Three, we receive source information, i.e. the type of platform the vacancy was scraped from. Four, we receive vacancy information, containing the original job description.

Upon receiving the data, we perform further cleaning procedures. First, we link firm and vacancy information, especially in order to assign job descriptions to specific industries. Second, we use this linked data set to assign OJV to specific locations, preferably at the zip-code level. When zip-code level data is not available, we use information on the job site (i.e., city, town, or village).<sup>9</sup> For about 10% of vacancies we only observe the job site at a broader level, e.g., district-level. For the purpose of this paper we omit these observations and only use zip-code and job site information as we seek sufficiently precise information about the location of the workplace. Third, we create a unique taxonomy to measure skill demand, proxied by job activities demanded by firms. We describe this taxonomy and its consistency with the existing literature in more detail in section 2.3.

For our analysis, we focus on vacancies for regular work, i.e. full- or part-time. Thus, we remove vacancies seeking apprenticeships, trainees, and other types of irregular work. In particular, we drop vacancies for temporary employment as they are not representative of regular labor market developments.<sup>10</sup> Temporary employment agencies are special in the sense that their postings may be counter-cyclical: If labor demand is small, they may increase the number of persons in their applicant pool, and publish less postings if labor demand is high in the labor market. Therefore, job vacancies of temporary employment agencies distort demand for labour demand and show patterns that are incompatible with official statistics. Moreover, we keep only those vacancies for which we have firm-level information from the company registry. This way, we maintain a consistent sample for our analysis.

After cleaning and selecting the relevant data, we are left with 29 million job vacancies, comprising 297,000 firms and 2.8 million firm-month observations. In a final step, we perform a few more standard preprocessing steps on the job description. Specifically, we follow [Gentzkow, Kelly & Taddy \(2019\)](#) and preprocess the text data for the empirical analysis by (i) converting job descriptions with tokenization, (ii) removing stop words, and (iii) stemming words.

In section C.1 in Appendix C we provide external validity on our data quality by compar-

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<sup>9</sup>We know the zip code of the job site for about 60% of vacancies and the name of the city, town, or village for about 30% of vacancies. In some cases, two job sites have the same or vague names, e.g., *Frankfurt am Main* versus *Frankfurt an der Oder*. In these cases, we assign the vacancy to both cities and weigh both observations by half.

<sup>10</sup>See [Stops, Bächmann, Glassner, Janser, Matthes, Metzger & Müller, Christoph, Seitz, Joachim \(2021\)](#).



ing trends by time and industries to official job vacancy statistics. Overall, we demonstrate our OJV data depicts similar trends between 2017 - 2022 and covers all industries properly.

## 2.2 Regional Data and Local Labor Market Definition

We supplement our OJV data with regional characteristics to account for systematic differences between LLMs that may confound our analysis on local changes in task demand. These variables are taken from a regional administrative database, [Regionalstatistik.de](#) ([Regionalstatistik 2022/10/25](#)), and comprise various statistics at the county-level, such as local skill composition, socio-economic composition (age, gender, citizenship), industry composition, and the average local unemployment rate.

We define the relevant local labor market at a broader definition than county-level. Counties have administrative boundaries that do not necessarily reflect LLM in an economic context. For example, counties do not account for common commuting zones. Disregarding these movements may introduce spillovers and thus bias our results. We therefore aggregate the 402 counties into 141 broader LLM, following the classification of [Kosfeld & Werner \(2012\)](#), which has been used widely in research on LLMs in Germany, e.g. [Dauth, Findeisen, Suedekum & Woessner \(2021\)](#), [Hirsch, Jahn, Manning & Oberfichtner \(2022\)](#).

## 2.3 Task Data

Our access to the original texts of the vacancies allows us to have complete control over the data-generating process and develop our own, transparent skill taxonomy. In contrast, the existing literature uses classified information that has been preprocessed by the respective data provider ([Blanas & Oikonomou 2022](#)). For our taxonomy we collect job activities that have been frequently adopted in the existing task literature, either based on survey responses<sup>11</sup> or retrieved from the online portal BERUFENET, the German equivalent of the US O\*NET database<sup>12</sup>.

Subsequently, we follow the literature ([Autor, Levy & Murnane 2003](#), [Spitz-Oener 2006](#), [Storm 2022b](#)) and classify a variety of single activities into five broad task categories: (i) non-routine (NR) analytic, (ii) NR interactive, (iii) routine (R) cognitive, (iv) R manual, and (v) NR manual. NR analytic and NR interactive involve strong problem-solving skills and abstract thinking. In contrast, routine tasks are characterized by following explicit and easily codifiable rules. Lastly, NR manual requires physical labor pronounced in, for example,

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<sup>11</sup>For an overview of tasks used in the survey-based literature, see, e.g., [Spitz-Oener \(2006\)](#), [Gathmann & Schönberg \(2010\)](#), [Rohrbach-Schmidt & Tiemann \(2013\)](#), [Storm \(2022b,a\)](#).

<sup>12</sup>For an overview of tasks used in this literature, see, e.g., [Dengler, Matthes & Paulus \(2014\)](#).

basic services.

NR analytic and NR interactive involve strong problem-solving skills and abstract thinking. In contrast, routine tasks are characterized by following explicit and easily codifiable rules. Lastly, NR manual requires physical labor pronounced in, for example, basic services.

Figure 1 displays word clouds, illustrating the most important activities belonging to each of the above task groups. Overall, we consider the most important activities within each task group intuitive and in line with existing job task descriptions used in the literature. For instance, *analysis* and *development* are the two most important activities within the task group NR analytic, while activities in the realm of *human resource management* are the most important activities within the task group NR interactive. Regarding the routine task groups, *register* and *surveillance* are the most important activities within Routine cognitive and *preparation* and *production* are the most important activities within Routine manual. Lastly, *equipping* [machines] and *support* are the most important activities within NR manual.

[Figure 1 here ]

Next, we use these activities to construct our outcome variables. First, we count for each firm  $i$  located in LLM  $l$  the number of online vacancies that have been posted in month  $m$  in year  $t$ . Second, we count the number of times that task  $j$  has been posted across all vacancies. Third, we compute the average task intensity for each firm  $i$  by dividing the number of tasks by the number of overall vacancies posted.

For example, if firm  $i$  in LLM  $l$  posted 10 vacancies in January 2017 and we count a total of 50 NR interactive tasks in these postings, the absolute task intensity of NR interactive in  $i$  in January 2017 was 5. Performing this calculation for each of the five tasks gives us the full distribution of task intensities. To alleviate concerns regarding differential trends in firms' posting behavior - e.g., more postings, see Figure 8, or more task requirements - we calculate the relative task intensity  $T_{ijlmt}$  as follows:

$$T_{ijlmt} = \frac{\text{Number of tasks } j \text{ demanded by firm } i \text{ in LLM } l \text{ in month } m \text{ in year } t}{\text{Total number of tasks demanded by firm } i \text{ in LLM } l \text{ in month } m \text{ in year } t} \quad (1)$$

where  $j = 1, \dots, 5$  represents the five tasks defined above. This definition implies (i)  $T_{ijlmt} \in [0, 1] \forall j$  and (ii)  $\sum_j T_{ijlmt} = 1$ , thus describing the average relative importance of each task  $j$  in vacancies posted by firm  $i$ . For example,  $T_{NRI,ilmt} = 0.5$  implies 50% of all tasks demanded in vacancies by firm  $i$  at time  $t$  are interactive. Variations of this measure have been widely adopted in the task literature, making our results comparable to previous research (Antonczyk, Fitzenberger & Leuschner 2009, Storm 2022b, a).

[Figure 2 here ]

Figure 2 plots the average task intensity in our sample from 2017m1 - 2022m12. The two most important task groups are NR analytic and interactive, each representing 30% of all tasks. This observation is broadly consistent with survey-based data from the late 2010s (Storm 2022b), yet, also provides insights on near real-time trends in skill demand. The key takeaway from this illustration is a recent reversal in the relative importance of analytic and interactive tasks. Up until early 2019, the analytic task intensity ranged between 35-40%, while the interactive task intensity fluctuated around 30%. Since then, however, interactive tasks have become relatively more important, reaching 35% by the end of 2022—at the expense of analytic tasks (30% task intensity by 2022). The remaining routine- and manual-intensive task intensities have remained rather stable over time, ranging in task intensities between 10% (routine manual and NR manual) and 20% (routine cognitive). This observation is somewhat at odds with Arntz, Genz, Gregory, Lehmer & Zierahn-Weilage (2024), suggesting a recent decline in the importance of routine tasks based on survey data.

### 3 Methodology

In this section, we outline our empirical approach. We begin by describing our firm classification, in which we assign firms into distinct technology tiers, using information provided in their postings. Subsequently, we proceed by discussing our research design, a matched Diff-in-Diff estimation with continuous treatment. To this end, we provide a detailed discussion on model specification, identifying assumptions, and our matching procedure.

#### 3.1 Classification of Technologies and Firm Types

To classify firms subject to their level of digitization requires detailed information on technology use. Our data does not have information on actual technology adoption. Instead, we infer firms' *potential* adoption using the information provided in job vacancies. For brevity, we will highlight the key steps of our firm classification here.

##### 3.1.1 Technology Classification

We follow related literature (e.g. Genz, Gregory, Janser, Lehmer & Matthes (2021)) and distinguish between two broad classes of technologies: (i) "3.0 Technologies" and (ii) "4.0 Technologies". The former class comprises the first generation of digital technologies introduced in the early 1980s, such as Microsoft Office products, various programming software,

and industrial technologies such as Computer numerical control (CNC).<sup>13</sup> The latter class encompasses more recent digital technologies that have been introduced to mass markets in the 2010s. These technologies comprise, among others, AI and Cloud Technologies, and are characterized by greater degrees of connectivity than previous 3.0 technologies.

To begin with our classification, we first collect a comprehensive list of technologies from the European Skills, Competences, Qualifications, and Occupations (ESCO) framework ([ESCO \(European Skills/Competences, qualifications, and Occupations\) 2024](#)). ESCO provides a harmonized classification of skills, qualifications, and occupations, along with an extensive depiction of ICT technologies. While ESCO continuously updates its data and provides extensive coverage of 3.0 technologies, it lacks information on most recent technologies. In the second step, we therefore enrich this list of "ESCO-technologies". To get a more up-to-date view on recent 4.0 technologies, we add these types of technologies from state-of-the-art literature.<sup>14</sup> Subsequently, we use standard NLP techniques to preprocess our final list of technologies to make it suitable for econometric analysis.<sup>15</sup>

[Figure 3 here ]

In the third and final step, we classify our list of 905 technologies into 3.0 and 4.0 technologies. This step is crucial as it allows us to distinguish firms with different levels of digitization, given that firms with different technology use systematically differ from each other ([Acemoglu et al. 2022](#), [Genz et al. 2021](#)). To assist with this classification task, we use Chat GPT 4.0 after providing context on the goal of our study and detailed information on the difference between 3.0 and 4.0 technologies. Figure 3 displays the result of this exercise, showing word clouds for each type of technology. Next to some rather generic concepts, such as data and software, the most prominent 3.0 technologies are MS Office products, database-related technologies, and a variety of programming languages. In contrast, the most important 4.0 technologies are cloud technologies, machine learning applications, and various "smart" technologies (e.g. smart home, E-mobility).

### 3.1.2 Firm Classification & Descriptives

#### I. Firm Classification

Having identified and classified our key technologies, we now proceed to use this information to classify firms into technology tiers. To this end, we first scan our OJV data for

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<sup>13</sup>See [Genz, Gregory, Janser, Lehmer & Matthes \(2021\)](#) for a detailed discussion.

<sup>14</sup>Especially [Bloom, Hassan, Kalyani, Lerner & Tahoun \(2021\)](#) and [Chiarello, Fantoni, Hogarth, Giordano, Baltina & Spada \(2021\)](#).

<sup>15</sup>See [Gentzkow, Kelly & Taddy \(2019\)](#), [Ash & Hansen \(2023\)](#) for excellent reviews on these techniques.

references to either of our 905 specific technologies. For the purpose of this classification exercise, we limit ourselves to postings between January 2017 and February 2020, i.e. pre-COVID. We do so because we will use the COVID-outbreak as an exogenous shock for our identification strategy, described in detail in section 3.2.

In our empirical setup, we will assign firms different treatment status depending on their experience with digital technologies pre-COVID. Hence, we only use information available to us up until February 2020. Moreover, we focus on firms that have posted vacancies regularly two years before and after the initial COVID shock to alleviate concerns regarding compositional changes, e.g. because of firm exit or hiring freezes. Using this sample selection, we thus give the remaining firms three years time to provide us with relevant information on technology use based on their job descriptions.

We define a firm as "4.0 firm" if we find at least one reference to a 4.0 technology in their postings prior to February 2020. If we do not find such a reference, but we do find at least one reference to 3.0 technologies, we instead classify such a firm as "3.0 firm". In those cases in which we find neither reference, we classify a firm as "2.0" firm. Hence, this category serves as residual group for all firms we were not able to classify as 3.0 or 4.0 firms.

[Figure 4 here ]

How convincing is our classification procedure? We perform many validation exercises to test if our classification is consistent with related literature and well-known stylized facts. Notably, we find that around 20% of our firms are 4.0 firms, i.e. firms using frontier technologies (see Figure 4). 50% of firms are 3.0 firms, using digital technologies, but not recent frontier technologies yet. The remaining 30% are 2.0 firms, which we interpret as firms with only modest experience with digital technologies. This breakdown is remarkably similar to [Genz, Gregory, Janser, Lehmer & Matthes \(2021\)](#) who find almost the exact distribution based on a representative survey among German firms, lending credence to our classification exercise. Table 1 adds to this assessment, displaying summary statistics by firm type. For example, 4.0 firms tend to be larger, have higher revenues, and have more complex job requirements, consistent with the "Superstar firm literature" ([Autor, Dorn, Katz, Patterson & van Reenen 2020](#)).<sup>16</sup>

[Table 1 here ]

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<sup>16</sup>We performed further validity tests. In particular, we also show that 4.0 firms are concentrated in innovation hotspots in Southwest Germany as well as in ICT, Finance, and Professional Services sectors. All of this evidence is consistent with well-known stylized facts in the innovation literature ([Gathmann, Kagerl, Pohlen & Roth 2023](#), [Rammer 2022](#)), lending further credence to our classification strategy.

## II. Technology upgrading

We have recently learned that many firms invested in digital technologies over the last couple of years, solely because of the pandemic (Gathmann, Kagerl, Pohlen & Roth 2023, Barth, Bryson & Dale-Olsen 2022). Therefore, had COVID-19 not occurred, firms would have likely adopted technologies at a slower pace. While we do not observe firm investments into technologies, we can take advantage of the granularity of our OJV data, especially pertaining to actual technology use at the workplace. Since we have panel data, we can track firms over time and observe changes in their utilization of technologies. To identify such episodes, we flag the first reference to a digital technology in firms' job postings. Intuitively, we consider the timing of the first reference to a more advanced technology tier indicative of technological upgrading. For example, when we classify a firm initially as "3.0", this implies we have not detected references to more advanced 4.0 technologies yet. If said firm mentions such a 4.0 technology for the first time in their postings in, say, September 2020, we would interpret such an episode as technological upgrading.

To fix ideas, we create a dummy for the first month in which a firm references a technology that is more advanced than what has been previously mentioned in their postings. Counting these dummy variables over time, and for each firm type separately, allows us to test if the Pandemic-Push-Phenomenon also shows up in our data. In Figure 7 we summarize the results of this exercise.

[Figure 7 here ]

For example, the blue dashed line shows the share of firms that used to be a 2.0 firm, but would be re-classified as a 3.0 firm once we find the first reference to a 3.0 technology in their postings. In the years prior to the pandemic, this was the case for around 6% in any given month.<sup>17</sup> Since the pandemic, however, this share has increased by 1.5 pp., implying that 25% more firms are switching from 2.0 to 3.0 status ever since. Note further that this acceleration has been steady, suggesting these firms kept using the (for them) new technologies well beyond lockdown restrictions. Our descriptive evidence is thus consistent with the Pandemic-Push-Phenomenon, pointing to rising adoption of digital technologies among 2.0 firms since the pandemic. We see a slight increase in the share of firms who switch from 3.0 status to 4.0 status. However, these trends are much weaker, suggesting 2.0 firms' technology use has been most responsive to the COVID-induced disruptions.

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<sup>17</sup>Note the slight increase in the share of firms switching from 2.0 to 3.0 status between 2017 - 2018. Part of this increase can be attributed to the data-generating process as our data provider extended its search for vacancies in 2018. Hence, 2.0 firms were somewhat underrepresented in 2017. We aim to address this compositional change in our upcoming draft.

**III. Labor Demand** Having established our firm classification and stylized facts on technological upgrading, we now proceed to inspect trends in labor demand. Figure 5 displays the labor demand for each firm type over time. Note we indexed labor demand for each firm to the their first observation, thus creating a measure that captures dynamics in labor demand relative to the baseline period. This way, we account for scale effects (as large firms naturally post more vacancies). This graph shows rising labor demand for all firm types, but also different dynamics. Interestingly, the increase in labor demand is most pronounced among 4.0 firms, displaying a relative increase by more than 60% compared to 2017 levels. In comparison, we observe an increase in relative demand of about 50% for 2.0 firms and 30% for 3.0 firms. Our findings thus suggest a disproportionately strong shift in labor demand among frontier firms, which are already using the most recent generation of technologies. This observation is consistent with greater need for recruitment in response to technology adoption.

[Figure 5 here ]

#### IV. Skill Demand

Moving on, we present recent trends on skill demand. Figure 6 depicts new trends in task demand by firm type. A key observation is the recent increase in demand for interactive tasks, starting in 2021 and visible for each firm type. However, firms have compensated this task shift in different ways. Among 4.0 firms, the relative increase in interactive tasks comes primarily at the expense of analytic tasks (Panel 6a). In 2017, the analytic task content was about 10 pp. higher than the interactive content (40% vs 30%). By the end of 2022, however, we observe a task content of 35% for both groups, implying a convergence in terms of their relative importance within 4.0 firms.

In contrast, Panel 6c shows that 2.0 firms experienced a concurrent decline in demand for routine manual tasks (similar to the "de-routinization" phenomenon in [Arntz, Genz, Gregory, Lehmer & Zierahn-Weilage \(2024\)](#)), but also a slight increase in demand for analytic tasks. This observation suggests recent skill upgrading among 2.0 firms that coincides with the COVID-induced increase in technology upgrading (see Figure 7). We observe similar trends among 3.0 firms, albeit with weaker shifts (Panel 6b).

[Figure 6 here ]

In a nutshell, the descriptive evidence laid out in this section shows that our firm classification (i) displays stylized facts that are consistent with established findings in the literature, but on top of that (ii) adds heterogeneous insights into labor and skill demand. Importantly, the direction and size of these shifts in demand for labor and skills depend on firms' use



of technologies. In the next section, we build upon these insights to provide a rigorous econometric analysis.

## 3.2 Empirical Methodology

### 3.2.1 Diff-in-Diff with continuous treatment

For our empirical strategy we exploit the sudden COVID-induced rise in technological upgrading, which we have documented in the first section 3.1.2 and has also been referred to as the "Pandemic Push" (Gathmann, Kagerl, Pohlan & Roth 2023, Barth, Bryson & Dale-Olsen 2022). The disruption to workplaces, caused in the early stages of the pandemic, induced many firms to adapt to technologies that, by now in 2024, have become nearly ubiquitous for many workers (e.g. videoconferencing, collaborative technologies, AI-driven systems), see Bloom, Hassan, Kalyani, Lerner & Tahoun (2021) for a detailed discussion.

The key empirical challenge is the widespread impact of the pandemic. To some extent, all firms were affected by COVID-19. A standard Diff-in-Diff with binary treatment is thus not applicable because there is no natural control group. We thus adopt an approach with continuous treatment, in which firms are treated with differential intensity. The overarching idea of a continuous treatment is that standard treatment effects can be split into a *level effect* and *slope effect*. The level effect captures the treatment of some dose  $d$ . In a standard binary setting, the level effect identifies the desired treatment effect (provided assumptions are satisfied). In our setting, however,  $d$  reflects the sudden COVID-shock, which affected all firms. We therefore additionally need the slope effect for identification. This effect represents the causal response to an incremental change in  $d$ , evaluated at some level  $d$ . In our setting, the slope effect captures the idea that firms in distinct technology tiers received different doses  $d$  of the same underlying shock, implying differential treatment intensity. We refer the interested reader to Callaway, Goodman-Bacon & Sant'Anna (2021), de Chaisemartin, d'Haultfoeuille, Pasquier & Vazquez-Bare (2022) for excellent recent reviews of these new methods.

Specifically, we argue that firms' treatment intensity depends on their underlying technology use. Firms that had already been using new digital technologies prior to the pandemic, are arguably less affected. For example, if they already made use of collaborative technologies by 2019, then the pandemic should have not altered their technology use too much. In contrast, firms which, based on the information provided in job postings, had no prior experience with recent digital technologies, may now have suddenly been "forced" to use these technologies. This argument implies that 2.0 firms should have experienced greater treatment intensity than more advanced firms (3.0 and 4.0). We view our descriptive evidence

on differential technology upgrading from section 3.1.2 consistent with this idea.

With our treatment definition in mind, we then estimate the following baseline model:

$$\underbrace{Y_{jimt}}_{\text{Task Demand}} = \underbrace{\lambda_i + \mu_m}_{\text{Two-Way FE}} + \underbrace{\beta_j \times Post_t \times D2_i}_{\text{Treatment: 2.0 Firm}} + \delta X_{ijt} + \epsilon \quad (2)$$

where  $i$  represents firms,  $j \in (1, \dots, 5)$  reflects task groups,  $l \in (1, \dots, 141)$  reflects labor market regions,  $m \in (1, \dots, 12)$  reflects calendar months, and  $t \in (2017, \dots, 2020)$  reflects years.  $Y_{jimt}$  reflects our outcome variables —labor demand and skill demand for each task group  $j$ . The vector  $\mathbf{X}_{lmt}$  comprises various controls at the LLM-level to account for confounding factors that may affect local task demand.<sup>18</sup> Moreover,  $Post_t$  is an indicator for the post-COVID period, and  $D2_i$  denotes the continuous treatment status of 2.0 firms. To control for unobserved heterogeneity across firms and time, we also include fixed effects for labor market region (LMR,  $\lambda_l$ ) and months ( $\mu_m$ ). Having firm-level panel data with detailed information on technology use is a great advantage compared to the survey-dominated existing literature, as these studies only leverage cross-sectional variation in technology use (Arntz, Genz, Gregory, Lehmer & Zierahn-Weilage 2024, Gathmann, Kagerl, Pohlen & Roth 2023, Genz, Gregory, Janser, Lehmer & Matthes 2021).

The key parameter of interest is  $\beta_j$ , which captures the heterogeneous treatment effect of the COVID-induced increase technological upgrading on labor demand and skill demand  $j$ . This parameter thus allows firms’ responses to vary with underlying technology use.

An obvious key concern is selection as firms’ treatment assignment is non-random. Since we only have limited firm-level data that varies over time, we can only effectively control for regional differences over time. This data limitation thus does not allow us to properly control for selection concerns. To provide remedy for non-random selection of firms into the treatment group, we perform a matching procedure. This way, we compare firms with similar observables pre-COVID. We discuss our matching procedurs in more detail in section 3.2.3. Moreover, we define February 2020 as reference unit. All coefficients must thus be interpreted relative to the month before the pandemic started. We cluster standard errors at the LMR-level to account for serial correlation at more aggregated levels.

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<sup>18</sup>We include the following controls: share of college graduates, share of workers with completed vocational schooling, share of workers with neither ob above schooling requirements, share of different age groups (six age bins), share of workers with foreign citizenship, share of female workers, industry composition (1-digit, 13 industries), unemployment rate, technology differences (measured via share of vacancies in LLM that offer WFH option).

### 3.2.2 Identifying assumption

In a setting with continuous treatment, the identifying assumptions for a Diff-in-Diff estimation are different from those in a standard binary setting. We now outline the key assumptions and how we address them in our empirical strategy. Overall, our strategy relies on five assumptions (see [Callaway et al. \(2021\)](#) for an excellent discussion):

#### 1. Strong parallel trends

This assumption states that, absent the Covid-induced increase in technological upgrading, skill demand among our firms would have followed parallel trends. Hence, in the absence of treatment, firms with different levels of digital intensity would have experienced similar trends in skill demand. This assumption is a stricter version of the standard parallel trends assumption because it accounts for varying degrees of treatment intensity. We aim to validate this assumption twofold. First, we apply a matching approach to address selection as firms with differential technology use likely also differ in other characteristics (see our detailed discussion in section [3.2.3](#)).

Second, we aim to estimate exposure response functions for the pre-COVID period and check whether there are (different) pre-trends for different firm types, similar to [Ben Yahmed et al. \(2022\)](#). This strategy will allow us to determine the relationship between differential exposure to digitalization and task demand at different points in time. Specifically, we aim to plot our task demand measures along the distinct technology tiers at different points in time to assess whether the exposure-response profile to digitalization has remained constant over time.<sup>19</sup>

#### 2. No Anticipation Effect

This assumption asserts that firms did not change their skill demand in anticipation of the COVID-19 and the following increase in technology use. In other words, any changes in skill demand are responses to the pandemic and the ensuing Pandemic Push—but not anticipatory actions. We do not consider anticipatory effects a likely threat to identification as the pandemic was a sudden shock that most people did not see coming (at least in the magnitude experienced).

#### 3. Conditional independence

This assumption asserts that there should be no unobserved selection into technology groups. We address this concern twofold. On the one hand, our panel data allows us

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<sup>19</sup>In this current draft we focus on the first approach, using matching to make firms more comparable. We are currently working on the second part, the construction of exposure-response profiles, and will incorporate these tests in our upcoming draft.

to include firm FE and thus account for unobserved heterogeneity, which might give rise to selection. On the other hand, our matching procedure addresses remaining concerns as we compare task demand among firms within the same broad industry, and with similar pre-treatment characteristics at the firm-level (revenue, workforce, age) as well as LMR-level (skill composition, socioeconomic composition, unemployment). Conditional on these strategies, we argue treatment levels should be as good as random.

#### 4. Common Support

This assumption ensures that there is a sufficient range of digital intensities among the firms, including firms with no or minimal digitalization. We need to satisfy this assumption to ensure that our propensity scores are non-zero for every treatment intensity and do not become extreme. We check for common support by trimming extreme weights for robustness purposes.

#### 5. Stable unit treatment value assumption (SUTVA)

This assumption asserts that technology use in one firm should not affect other firms after being treated, hence ruling out spillover effects. Given our relatively short time horizon (2017-2023), we consider this assumption innocuous in our setting as firms likely need more time to adjust their technology use and own skill demand in reaction to other firms' actions.

### 3.2.3 Matching and Definition of Treatment

Our data lacks time-varying information at the firm-level, which is essential to control for non-random selection into treatment. We thus implement a matching procedure to alleviate these concerns by creating a control group that is statistically similar to treated firms (based on pre-COVID characteristics in 2017). Specifically, we employ a two-stage matching approach, which draws upon established methodologies in the literature (Blien, Dauth & Roth 2021, Arntz, Ivanov & Pohlen 2022, Hethy-Maier & Schmieder 2013). The first stage of the process involves exact matching based on industry classification at the 1-digit level. This step ensures that firms are compared within the same broad industry category, acknowledging the significant role of industry characteristics in technology adoption (see e.g. Gathmann & Grimm (2022)). In the second stage we combine coarsened and Propensity Score (PS) matching. The coarsening aspect of our matching approach focuses on firm-specific characteristics, such as the age of the firm, workforce size, and revenue, to enhance the quality of our matches. Regarding PS matching, we use nearest neighbor matching (NNM) to select the most comparable control firm and focus on LMR-specific characteristics.<sup>20</sup> These local

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<sup>20</sup>Using NNM implies that we perform matching with replacement. Therefore, a control firm can serve as comparison group for multiple treated firms. This way, we can raise the likelihood of finding a suitable

factors include unemployment rates and the local composition concerning workers’ age structure, education level, nationality, gender, and industrial employment shares. Combined, our matching approach allows us to construct a counterfactual scenario in which treated (2.0) and control firms (3.0, 4.0) are comparable in terms of both firm-specific and local labor market characteristics.

[Table 2 here]

To assess the quality of our matching procedure, we report our results on covariate balancing in Table 2. We are able to match treated and control groups well in terms of LMR-level characteristics. In terms of firm-level characteristics, however, some disparities remain. Especially size differences between treated (2.0) and control firms (3.0, 4.0) remain, both, in terms of workforce size and revenue. This observation makes sense as technologically more advanced firms tend to be larger (Autor, Dorn, Katz, Patterson & van Reenen 2020). While our current matching approach still has some deficiencies, we are able to reduce many selection concerns, for example pertaining to firm age and regional factors. We are thus confident that our empirical approach provides informative results on firm-specific responses to digitalization. Notwithstanding, we recognize the remaining concerns and are currently implementing alternative, possibly superior, matching approaches, including more flexible non-parametric approaches based on a generalized PS (Fong, Hazlett & Imai 2018).

## 4 Results

In this section we present our main findings. We begin with results on labor demand, showing how firms’ posting behavior responded differentially to the COVID-induced increase in technology upgrading subject to their pre-existing technology use. This analysis captures adjustments at the extensive margin of labor demand. Subsequently, we discuss our results at the intensive margin, i.e. differential changes in skill demand. Lastly, we briefly discuss extensions to our analysis, which we will add in an updated version of our draft.

### 4.1 Labor Demand

A vast literature has documented the cyclicity of labor demand, notably in response to large economic shocks, such as the Great Recession (e.g. Hershbein & Kahn (2018), Modestino, Shoag & Ballance (2019)) or COVID-19 (e.g. Forsythe, Kahn, Lange & Wiczer (2020a)). What is unknown, however, is to what extent firms’ technology use moderates this channel.

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match for treated firms.

Using our firm classification into distinct technology tiers, allows us to provide novel evidence on this channel.

[Table 3 here ]

Table 3 reports our estimates, displaying heterogeneous treatment effects of the COVID-induced rise technological upgrading on firms' labor demand. Our baseline specification uses weights from our matching procedure to account for selection into treatment. We also report unweighted specifications for comparison. In the first model we use the number of postings per month as outcome variable. This specification yields a negative estimate of -1.3. Accordingly, labor demand among treated 2.0 firms decreased by 1.3 vacancies since 2020, relative to 3.0 and 4.0 firms. This result suggests the "rebound effect" in labor demand following the initial collapse has been less pronounced among less digital firms.

Yet, this specification influenced by size effects as 3.0 and 4.0 firms tend to be larger. Therefore, higher labor demand among this broad group is mechanical to some extent. To circumvent this confounding factor, we also use a normalized labor demand measure in column 2. In this model, we set the number of firm-specific postings equal to 1 for the first month in which we observe a firm. All subsequent postings are then set relative to this benchmark, thereby removing level differences. This modification yields qualitatively the same results, implying an estimate of -0.6.

Taken together, our results show that more digital firms expanded their labor demand more rapidly during the pandemic push era. Our findings complement existing findings in the literature. For example, [Gathmann, Kagerl, Pohlen & Roth \(2023\)](#) show that employment among non-investing German firms was mostly adjusted by reduced hiring rather than layoffs. While the share of firms moving from 2.0 to 3.0 status has been accelerating since the pandemic (see Figure 7, many of those firms have remained 2.0 firms. Moreover, 2.0 firms tend to be smaller and are thus likely to be financially more constrained to invest into new technologies. The relative drop in labor demand among 2.0 firms (compared to 3.0 and 4.0 firms) is thus consistent with reduced hiring as a coping mechanism during the pandemic.

## 4.2 Skill Demand

While adjustments in labor demand provide valuable insights on firm-specific responses to rising digitalization, this extensive margin may mask other, more subtle adjustment mechanisms. In particular, implications for firms' skill demand are unknown. In light of acute labor shortages and high level of skill mismatch in many modern economies ([Güvenen, Kuruscu, Tanaka & Wiczer 2020](#)), however, this channel has high relevance and important policy implications. For this reason, we now turn to inspecting this intensive margin.

To shed light on this mechanism, we use our skill measures as outcome variables, but otherwise repeat our analysis from the previous section. Table 4 summarizes our results, depicting each of the five task groups separately in columns (1)-(5). Indeed, we find evidence for substantial task shifts. In particular, treated 2.0 firms have increased their demand for routine cognitive (+ 1.9 pp) and NR manual tasks (+2.1 pp) —primarily at the expense of routine manual tasks (-3.7 pp).

[Table 4 here ]

To put these results into perspective, we also report the gap in task intensities between treated (2.0) and control firms (3.0/ 4.0) prior to treatment, allowing us to quantify catch-up effects. For example, prior to the pandemic, 19% (15%) of all tasks among 2.0 (3.0/4.0) firms were routine cognitive activities, implying a gap of 4 pp. between treated and control firms. Ever since, however, 2.0 firms increased their routine cognitive task intensity by about 2 pp. on average. Therefore, this group of firms closed the pre-treatment task gap in routine cognitive activities by 50%. Following similar logic, we find an increase in the NR manual task gap by 67% and a decrease the routine manual task gap by 80%.

In sum, 2.0 firms’ skill requirements have become less manual-intensive on average during the pandemic push era. The net effect with respect to the two manual task groups is sizeable with a combined estimate of -0.016. Considering both manual task groups added up to about 0.3 prior to treatment, our results imply a drop in the overall manual task intensity of about 5% (0.016/0.3). The implication is that 2.0 firms’ skill requirements have become cognitively more demanding.

Interestingly, however, we find no significant effect for either of the two abstract tasks (analytic and interactive). This result is somewhat surprising, considering the broad convergence in analytic and interactive task intensities, reported in Figure 2. While this trend can be observed for all firm types, the convergence is especially pronounced among 4.0 firms (see Figure 6)

One possible explanation for our null estimates may be our treatment definition. In our baseline analysis we treat 2.0 firms because we have identified these firms as those most strongly affected in terms of their technology use since 2020. Yet, this treatment definition may be too narrow. We thus perform a robustness exercise in which we re-define our treatment. In this exercise, we treat both, 2.0 and 3.0 firms, thereby using 4.0 firms as control group. For this purpose, we re-run our matching procedure in order to assign new weights to the newly defined treatment group. Running this updated matching procedure provides similar insights as in our baseline approach (see Table 5). While our matching approach works well for regional characteristics, we are still left with some imbalances pertaining to



some of the firm-level characteristics (sales, workforce). Nonetheless, as stated previously, our current matching approach provides some remedy against selection into treatment, thus providing informative insights. Using this updated treatment definition, we indeed find different task shifts (Table 6). In particular, this refined specification has two key takeaways.

[Table 5 here ]

First, we find that the newly defined treatment group —2.0 and 3.0 firms—have increased their demand for analytic tasks by 5.5 pp., relative to 4.0 firms. Compared to the pre-pandemic task gap of 11 pp., this result implies that 2.0/3.0 firms have closed this task gap by 50%. Put differently, these firms have raised their skill requirements with respect to abstract tasks, closer to the level of more advanced 4.0 firms. Since our model identifies these estimates in response to more intensive use of digital technologies, our results are consistent with the skill-complementarity of new technologies (Krusell, Ohanian, Ríos-Rull & Violante 2000b, Kogan, Papanikolaou, Schmidt & Seegmiller 2023).

Second, the increase in demand for analytic tasks among 2.0/3.0 firms has come at the expense of interactive tasks. This result is interesting because all firms, regardless of technology tier, have had comparable task intensities with respect to interactive activities prior to the treatment (i.e. pre 2020). Ever since, however, 4.0 firms have become substantially more intensive in interactive tasks. While speculative at this moment, our results are consistent with strong complementarities between 4.0 technologies, such as AI, and interactive skills. These technologies can perform cognitively more demanding tasks than 3.0 technologies (e.g. autonomous programming) and are more connective. More intensive use of 4.0 technologies may thus facilitate task shifts away from analytic activities, instead more towards interactive ones.

[Table 6 here ]

### 4.3 Extensions and Future Outlook

In our current draft we have established the validity of our our data preparation, including the firm classification into technology tiers, and provided baselines results for our proposed methodology. We are currently implementing several steps to validate and enhance the depth of our analysis. In our upcoming draft, we will thus incorporate the following steps. First, we will provide estimates on dynamic heterogeneous treatment effects to study adjustments over time in more detail. Second, we will incorporate different weighting schemes to improve our matching procedure. While our current approach (incl. propensity score matching) is well-established and easy to implement, it has some notable disadvantages, e.g., restrictive

assumption on functional form. Non-parametric approaches, such as those using a generalized score (Fong, Hazlett & Imai 2018), are more flexible in this regard.

Third, we will shed light more light on underlying mechanisms, driving our results, e.g. the rise of Work-From-Home, institutional factors (such as short-time work), and compositional changes (e.g. shifts in occupational composition). Lastly, we also aim to provide insights on aggregate implications. To this end, we will aggregate our indicators for labor and skill demand, alongside the distribution of firm types (2.0, 3.0, 4.0), at the occupation-region level (144 occupations  $\times$  141 regions = 20,304 local labor markets). Subsequently, we merge these aggregated indicators to administrative data from the Institute of Employment Research (IAB). The evidence from our analysis suggests rising labor demand across firms and an increase in skill demand. Basic economic theory then suggests a stronger increase in wages and possibly occupational shifts in local labor markets disproportionately affected by these shifts. By Spring 2024, the administrative data from the IAB will be updated to also incorporate the year 2022. We will thus soon be able to link our OJV data for our entire time horizon (though will also provided updated descriptive analysis, including the full year 2023) in order to test our hypotheses.

## 5 Conclusions

The COVID-19 pandemic has contributed to an acceleration in digitalization as many firms were forced to adapt to the "New Normal", yet, with unknown consequences on work processes. In this paper we use German monthly online job vacancies data from 2017m1 - 2022m12 to study the diffusion of digital technologies over time and provide causal evidence on the impact of rising digitalization on demand for labor and skills. To operationalize our analysis, we assign a comprehensive list of 905 technologies into two distinct technology tiers: (i) 4.0 technologies, comprising, e.g. AI and Cloud technologies, and (ii) 3.0 technologies, comprising, e.g. MSOffice products and CNC). Subsequently, we assign firms into three distinct technology tiers based on references to above technologies in their job postings. We distinguish between (i) 4.0 firms, using, among others, cutting-edge 4.0 technologies, (ii) 3.0 firms, not yet using 4.0 technologies, and (iii), 2.0 firms, not using 3.0 nor 4.0 technologies extensively.

Taking advantage of the high-frequency panel structure of our data, we first demonstrate more intensive use of technologies coinciding with the post-COVID period (i.e beginning in 2020). In particular, we document that the frequency at which 2.0 firms are being elevated to 3.0 status has increased by 25% relative to pre-pandemic levels. In comparison, we find a more modest acceleration of firms moving from 3.0 to 4.0 status. Hence, our analysis suggests

that the recent increase in technology upgrading may have made digital technologies more accessible and thus helped lesser-advanced firms to catch up.

To study their causal impact on labor and skill demand, we exploit this COVID-induced rise in technology upgrading and perform a matched Diff-in-Diff estimation to study heterogeneous responses in labor and skill demand. A key identification challenge is lack of proper control groups, since all firms were affected by the pandemic to some extent. To overcome this challenge, we propose a continuous treatment approach in which firms receive differential treatment intensity subject to their technology tier.

Our main analysis provides novel insights on the implications of technological upgrading on labor and skill demand. First, we find that all firms expanded their labor demand substantially since 2020. However, this rebound from the COVID-induced collapse in labor demand (Forsythe, Kahn, Lange & Wiczer 2020a), was primarily driven by 4.0 firms. Firms with most advanced technologies thus increased their labor demand disproportionately, suggesting great need for recruitment in order to implement recent 4.0 technologies. Second, we show widespread upskilling among firms. But importantly, firms display different adjustment mechanisms depending on their technology tier. On the one hand, 2.0 and 3.0 firms have raised their demand for analytic skills by up to 19%, relative to pre-pandemic levels. To make these adjustments, those firms substituted away primarily from interactive skills. On the other hand, 4.0 firms have increased their demand for interactive skills by up to 12%. Our results are thus consistent with strong complementarities between recent 4.0 technologies and social skills.

Our results have important policy implications and provide many avenues for future research. We provide new contemporaneous evidence on the diffusion of digital technologies, showing that especially recent 4.0 technologies require greater need for recruitment. In light of rising levels of digitalization, these needs are likely going to intensify, yet, may be hampered by acute labor shortages —especially in IT-related jobs (BMWK 2022). Shortages may further be exacerbated due to a concurrent increase in skill requirements. We demonstrate substantial heterogeneities in skill demand subject to a firms’ underlying technology use, possibly exacerbating existing matching inefficiencies (Forsythe, Kahn, Lange & Wiczer 2020b). Future research can guide this process. For example, a more detailed analysis of skills would help to identify key competencies and provide more sophisticated policy recommendations. Similarly, we focus on skill demand. However, skill supply is equally important to fully comprehend the labor market effects of recent technologies. To date, there are only a few studies providing detailed assessments on recent changes in skill supply (e.g Biasi & Ma (2023)). Combining these strands of the literature would help resolve empirical challenges pertaining to the estimation of matching qualities in response to changing skill requirements.

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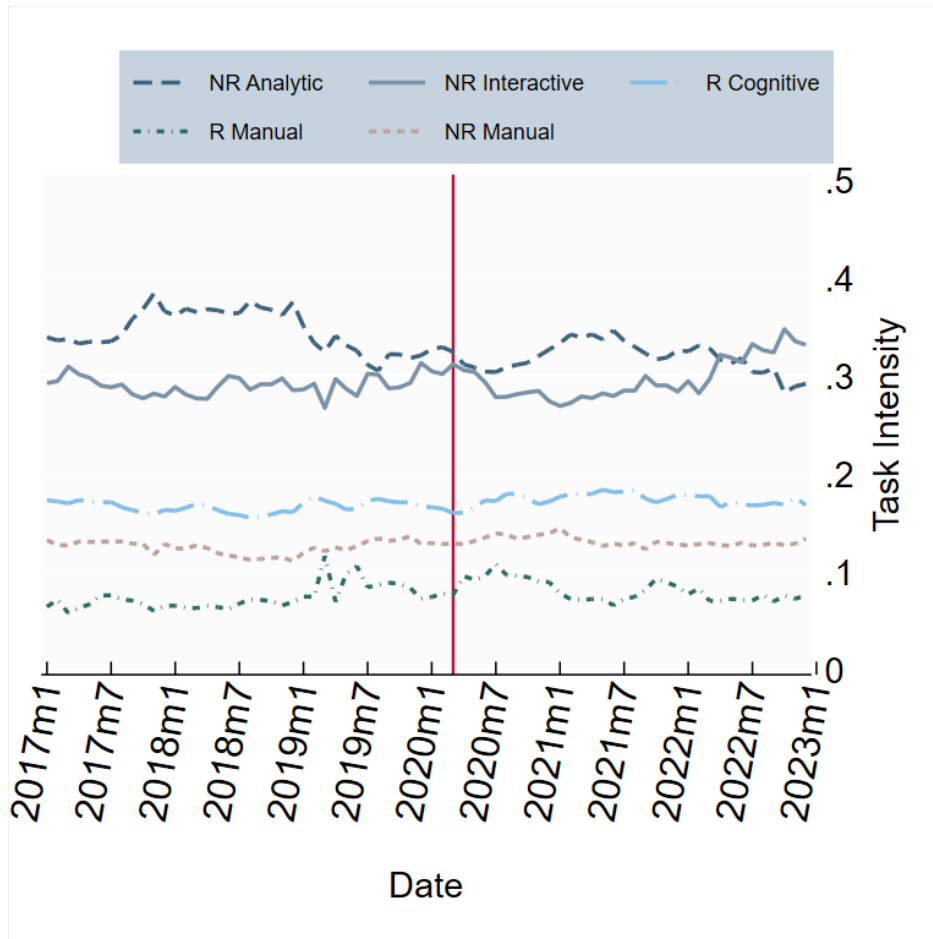


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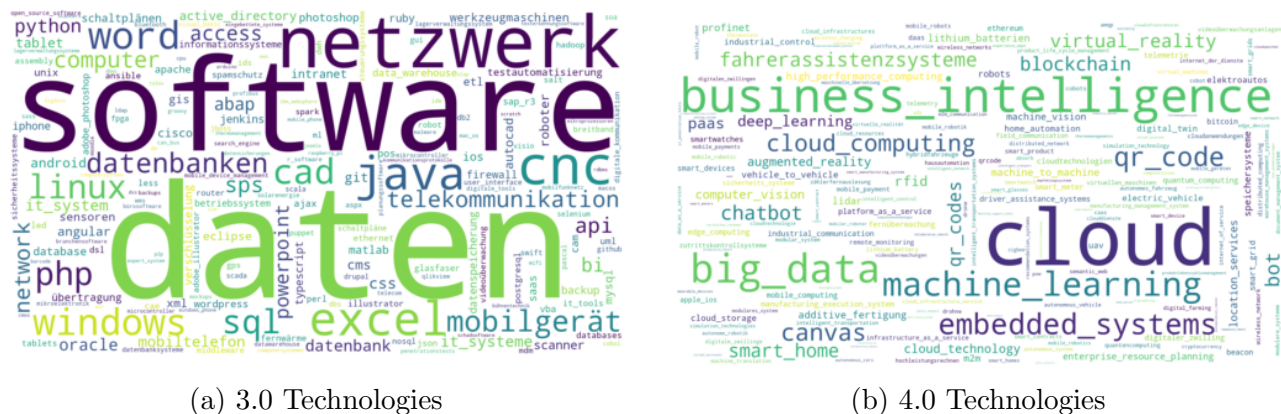
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NOTE. —This graph reflects skill demand for each of our five task groups and captures their relative importance. For example, the value of 0.3 for NR interactive tasks in early 2017 implies that 30% of all skill requirements were interactive.

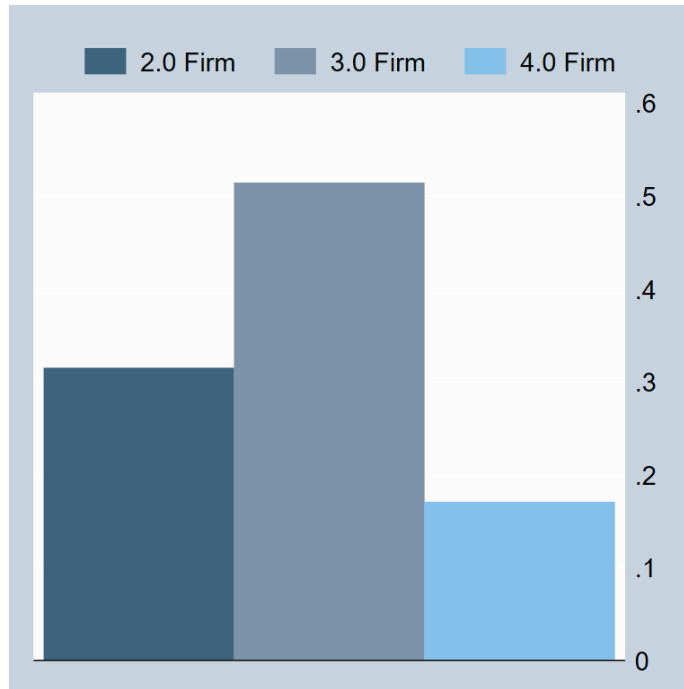
Figure 2: Skill Demand derived from German online job vacancies, 2017-01 - 2022-12



(a) 3.0 Technologies

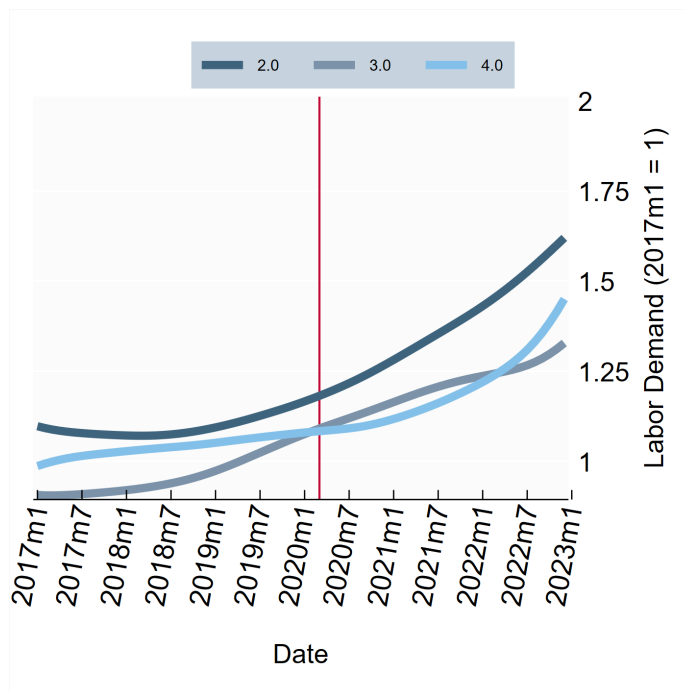
(b) 4.0 Technologies

Figure 3: Word cloud of 3.0 and 4.0 Technologies



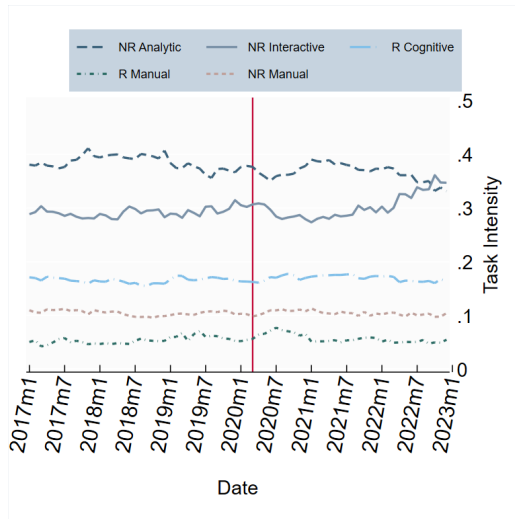
NOTE. —This graph shows the distribution of firm types in our vacancy data. Firms are assigned into a technology tier based on references to distinct technologies in their job postings. Accordingly, 20% of all firms are 4.0 firms, 50% are 3.0 firms, and 30% are 2.0 firms.

Figure 4: Firm-level Distribution of Technology Tiers



NOTE. —This figure displays labor demand for each of our three firm types. Labor demand is indexed to be = 100 in 2017 and then subsequently measured relative to this baseline. This way, we remove level differences in labor demand between firm types.

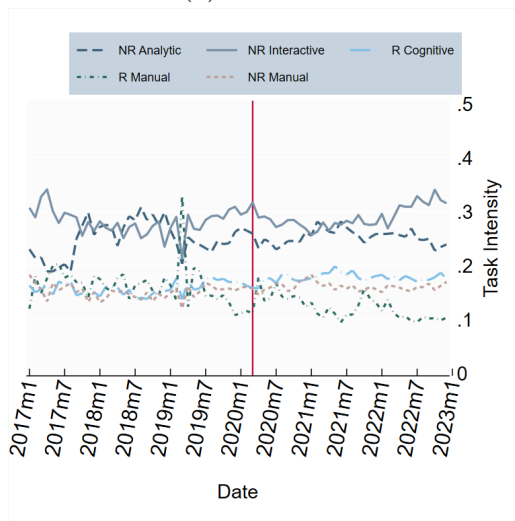
Figure 5: Labor Demand derived from German online job vacancies, by Firm Types (2017 = 100), 2017 - 2022



(a) 4.0 Firms



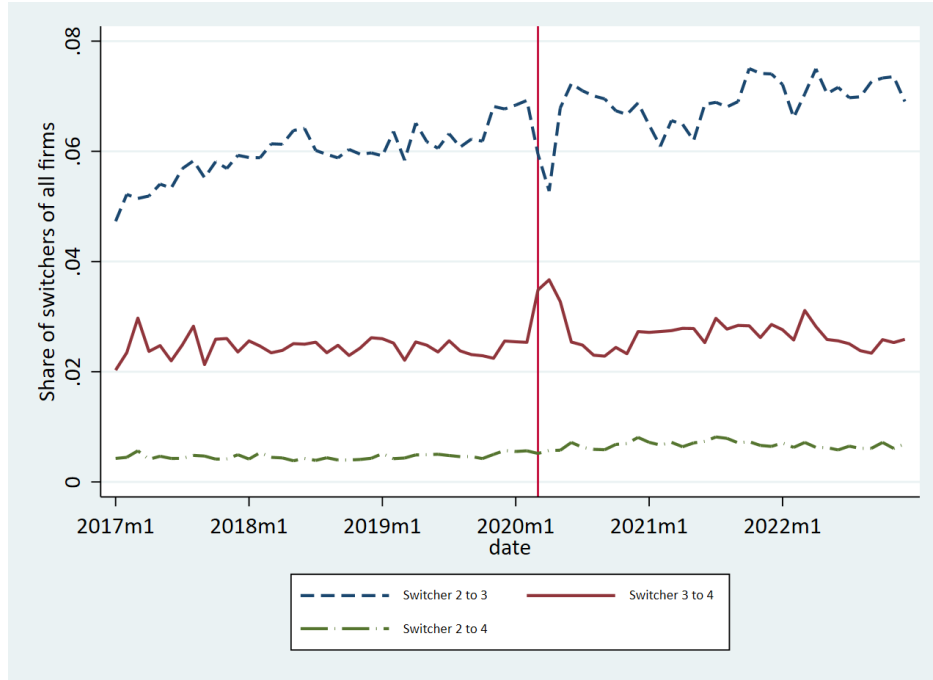
(b) 3.0 Firms



(c) 2.0 Firms

NOTE. —This graph reflects skill demand for each of our five task groups, separately for the three firm types. For example, the value of 0.3 for NR interactive tasks in early 2017 implies that 30% of all skill requirements were interactive.

Figure 6: Trends in Skill Demand by Firm Types, 2017 - 2022



NOTE. —This figure illustrates the share of firms that were elevated to a higher technology tier based on references to new technologies in their postings. For example, a value of 0.06 for 2.0 firms implies that 6% of these were elevated to 3.0 status in that particular month.

Figure 7: Share of firms switching into higher technology tiers, 2017 - 2022

## B Tables

Table 1: Summary Statistics: By Technology Tiers (2017 - 2022)

	(1)	(2)	(3)
	4.0 Firms	3.0 Firms	1.0/2.0 Firms
Firm Age	21.82	22.37	21.73
Avg. No. Job Postings	10.68	4.91	2.76
Workforce size	1815.16	589.71	209.50
Revenue	199,068.44	81,642.05	33,684.72
NR Analytic Intensity	0.40	0.31	0.24
NR Interactive Intensity	0.27	0.26	0.25
Routine Cognitive Intensity	0.13	0.16	0.19
RoutineManual Intensity	0.11	0.15	0.18
NR Manual Intensity	0.09	0.12	0.14
Share of OJV w/ technology: 3.0	0.58	0.44	0.18
Share of OJV w/ technology: 4.0	0.19	0.02	0.02
Observations	648,459	1,009,035	288,546

Table 2: Matching: Covariate Balancing (Treated: 2.0 Firm)

	Treated (2.0)	SD	Control (3.0/4.0)	SD
Age	21.49	15.22	22.73	13.00
Age Sq.	693.40	1315.80	685.73	994.01
Workforce size	276.07	1085.03	391.47	1880.80
Revenue	56,482.22	96702.99	82,095.84	168636.12
Unemployment	5.36	1.80	5.36	1.80
Share low-skilled workers	0.13	0.03	0.13	0.03
Share high-skilled workers	0.18	0.06	0.18	0.06
Share female workers	0.46	0.02	0.46	0.02
Share foreign workers	0.12	0.05	0.12	0.05
Share workers aged < 20	0.02	0.01	0.02	0.01
Share workers aged 20-30	0.08	0.01	0.08	0.01
Share workers aged 30-50	0.44	0.02	0.44	0.02
Share workers aged 50-60	0.26	0.01	0.26	0.01
Share workers aged 60-65	0.08	0.01	0.08	0.01
Share workers aged > 65	0.01	0.00	0.01	0.00
Observations	247909		10148	

Table 3: Results on the Impact of Technological Upgrading on Labor Demand (Treated: 2.0 Firm)

	Dependent Variable:	
	OJV per month	OJV per month (w/o scale effect)
2.0 Firm	-1.300*** (0.095)	-0.603*** (0.105)
2.0 Firm (unweighted)	-1.358*** (0.108)	-0.571*** (0.064)
Controls	✓	✓
Observations	1,453,558	1,424,249
R-squared	0.468	0.404

Clustered Standard errors in parentheses

\*  $p < 0.05$ , \*\*  $p < 0.01$ , \*\*\*  $p < 0.001$

NOTE. —Controls include local variables, such as unemployment and local composition wrt: workers' age structure, education, nationality, gender, and industrial employment shares. Treated 2.0 firms are matched to a control 3.0/4.0 firm within the same 1-digit industry and based on firm characteristics (age, sales, workforce) and above local characteristics.



Table 4: Results on the Impact of Technological Upgrading on Skill Demand (Treated: 2.0 Firm)

	Dependent Variable:				
	NRA	NRI	RC	RM	NRM
2.0 Firm	-0.013 (0.018)	0.010 (0.010)	0.019* (0.010)	-0.037* (0.019)	0.021*** (0.006)
2.0 Firm (unweighted)	0.011*** (0.002)	0.005 (0.003)	0.021*** (0.005)	-0.039*** (0.004)	0.003 (0.002)
Controls	✓	✓	✓	✓	✓
Avg. 2.0 Firm	0.24	0.25	0.19	0.18	0.14
Avg. 3.0/ 4.0 Firm	0.35	0.26	0.15	0.13	0.11
Observations	1,453,558	1,453,558	1,453,558	1,453,558	1,453,558
R-squared	0.48	0.47	0.47	0.58	0.49

Clustered Standard errors in parentheses

\*  $p < 0.05$ , \*\*  $p < 0.01$ , \*\*\*  $p < 0.001$

NOTE. — Controls include local variables, such as unemployment and local composition wrt: workers' age structure, education, nationality, gender, and industrial employment shares. Treated 2.0 firms are matched to a control 3.0/4.0 firm within the same 1-digit industry and based on firm characteristics (age, sales, workforce) and above local characteristics.

Table 5: Matching: Covariate Balancing (Treated: 2.0 & 3.0 Firm)

	Treated (2.0)	SD	Control (3.0/4.0)	SD
Age	21.04	14.20	22.20	13.47
Age Sq.	644.45	1102.58	674.11	1186.01
Workforce size	309.55	1132.93	539.71	2750.75
Revenue	64,744.27	96,933.37	108,443.37	198,814.61
Unemployment	5.35	1.80	5.25	1.77
Share low-skilled workers	0.13	0.03	0.13	0.03
Share high-skilled workers	0.18	0.06	0.18	0.06
Share female workers	0.46	0.02	0.46	0.02
Share foreign workers	0.12	0.05	0.13	0.05
Share workers aged < 20	0.02	0.01	0.02	0.01
Share workers aged 20-30	0.08	0.01	0.08	0.01
Share workers aged 30-50	0.44	0.02	0.45	0.02
Share workers aged 50-60	0.26	0.01	0.26	0.02
Share workers aged 60-65	0.08	0.01	0.08	0.01
Share workers aged > 65	0.01	0.00	0.01	0.00
Observations	247909		10148	

Table 6: Results on the Impact of Technological Upgrading on Labor Demand (Treated: 2.0 & 3.0 Firm)

	Dependent Variable				
	NRA	NRI	RC	RM	NRM
2.0/3.0 Firm	0.055*** (0.017)	-0.033** (0.015)	-0.005 (0.005)	0.001 (0.008)	-0.017*** (0.004)
2.0/3.0 Firm (unweighted)	0.006** (0.003)	-0.008*** (0.001)	0.012*** (0.003)	-0.010*** (0.001)	0.000 (0.001)
Controls	✓	✓	✓	✓	✓
Avg. 2.0/ 3.0 Firm	0.29	0.26	0.17	0.16	0.12
Avg. 4.0 Firm	0.40	0.27	0.13	0.11	0.09
Observations	1,453,558	1,453,558	1,453,558	1,453,558	1,453,558
R-squared	0.42	0.42	0.34	0.42	0.39

Clustered Standard errors in parentheses

\*  $p < 0.05$ , \*\*  $p < 0.01$ , \*\*\*  $p < 0.001$

NOTE. —Controls include local variables, such as unemployment and local composition wrt: workers' age structure, education, nationality, gender, and industrial employment shares. Treated 2.0 & 3.0 firms are matched to a control 4.0 firm within the same 1-digit industry and based on firm characteristics (age, sales, workforce) and above local characteristics.

## C Appendix

### C.1 External Validity of OJV Data

Figure 8a shows the number of OJV over time by source platforms. Overall, we see an increasing trend of the number of postings over time. In principle, this pattern can be explained by two factors. First, an increasing trend over time, i.e., firms may use their websites and job boards more often to post jobs online. Second, methodological changes, e.g., our private partner updates its scraping method and thus adds more sources. Rising levels of digitalization and the growing popularity of online job search by job seekers likely contribute to the increasing trend in OJV. We further find evidence that methodological changes matter as well since the composition of source platforms has changed over time. While (fee paying) job boards represented about 50% of all postings in 2017, their share increased to 70% by the end of 2021. This increase has come primarily at the expense of headhunters whose share decreased from 17% to less than 2% during the same time. These compositional changes demonstrate the need to validate the representativeness of OJV data.

[Figure 8 here ]

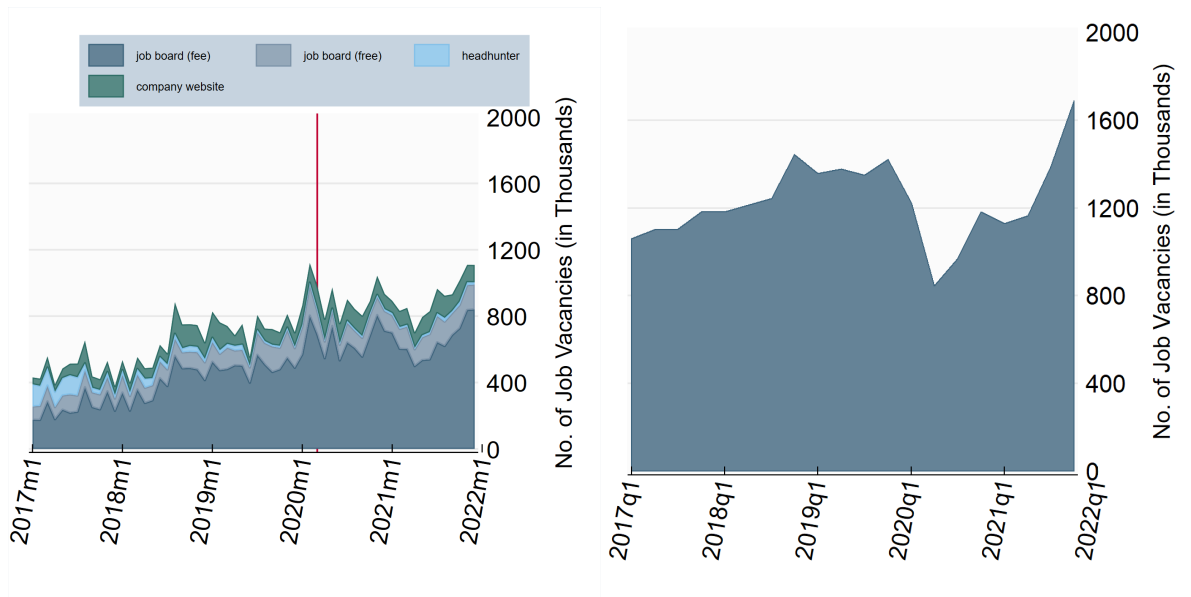
We follow common practice in the literature by comparing our OJV data with representative information on vacancies from official sources (Hershbein & Kahn 2018, Rengers 2018). Hershbein & Kahn (2018) compare characteristics of the job postings from Lightcast (formerly Burning Glass Technologies) with the Bureau of Labor Statistics’ Job Openings and Labor Market Turnover (JOLTS) survey and other data sources for the US at the aggregate level and by industries. Likewise, Rengers (2018) makes similar comparisons for Germany with data from the Federal Employment Agency (BA) and the IAB Job Vacancy Survey. Especially relevant for our purposes, the IAB Job Vacancy Survey is a representative survey and measures the aggregate labor demand and the recruiting behavior of firms in Germany since 1989, making it a well-suited survey for the analysis of recruitment processes (Gürtzgen, Lochner, Pohlman & van den Berg 2021). Below, we address these concerns by first studying aggregate trends and subsequently breaking down our OJV data by industries.

First, Figure 8 compares the (aggregate) evolution of vacancies taken from the IAB Job Vacancy Survey from 2017Q1 - 2021Q4 (2021 values are estimates) with our OJV data. Note that the IAB data reflects stock information, while our data is a measure for inflows of job postings. Despite these methodological differences, the two graphs display similar trends. Both display a steady increase in postings from 2017 until early 2020 with a sharp decrease at the onset of the pandemic in March 2020. While the stock of vacancies decreased by 40% between 2019Q4 and 2020Q2 based on the IAB Vacancy Panel, the inflows of vacancies in our OJV data decreased by 30% from December 2019 until June 2020. Both time series display a sharp subsequent rebound, leading to a catch-up to pre-COVID vacancy levels by the end of 2020. Moreover, the magnitude of the drop and rebound in job vacancies during the pandemic is consistent with previous findings in the literature from comparable countries, such as Australia (Shen & Taska 2020), Austria (Bamieh & Ziegler 2020), Sweden (Hensvik, Le Barbanchon & Rathelot 2021), the UK (Arthur 2021), and the US (Forsythe, Kahn, Lange & Wiczer 2020a). Hence, both, the cyclical nature of job postings and the magnitude in collapse and recovery of postings, lend credence to the validity of our data.

[Figure 9 here ]

Second, we divide our vacancies into six broad industries for ease of exposition: (i) manufacturing, (ii) retail & hospitality, (iii) information & communication, (iv) professional services, (v) personal services, and (vi) other industries. Figure 9 summarizes this industrial breakdown and provides three key takeaways. First, all industries are covered and well-represented in our data. Second, service industries, comprising professional and personal services, are the most important industry groups. On average, these broad industries comprise around half of all vacancies. Third, the industry composition in our data has become

more balanced over time. While the share of services decreased from 60% to 45% from 2017 until 2021, manufacturing and retail & hospitality have experienced rising coverage (in each industry from 15% to 20%). We interpret these developments favorably as the descriptive statistics support the quality of our data and its broadly representative nature. Part of this takeaway is attributed to the fact that our data begins in 2017. Internet access and especially online job search have already been common at this point, a distinguishing feature from the earliest possible OJV data in the US in the mid 2000s, a time during which online job posting was concentrated among professionals (Hershbein & Kahn 2018, Modestino, Shoag & Ballance 2019).



(a) OJV data, by source (Inflow)

(b) IAB Vacancy Panel (Stock)

NOTE. —Panel 8a displays the number of online job vacancies that are posted each month in our data, i.e., monthly inflows, broken down by the type of source platform. Panel 8b displays the stock of vacancies firms report to the IAB for each quarter. The values for 2021Q1 onward are estimates as final numbers are not available yet.

Figure 8: Number of Online Job Vacancies over Time, 2017-01 - 2021-12

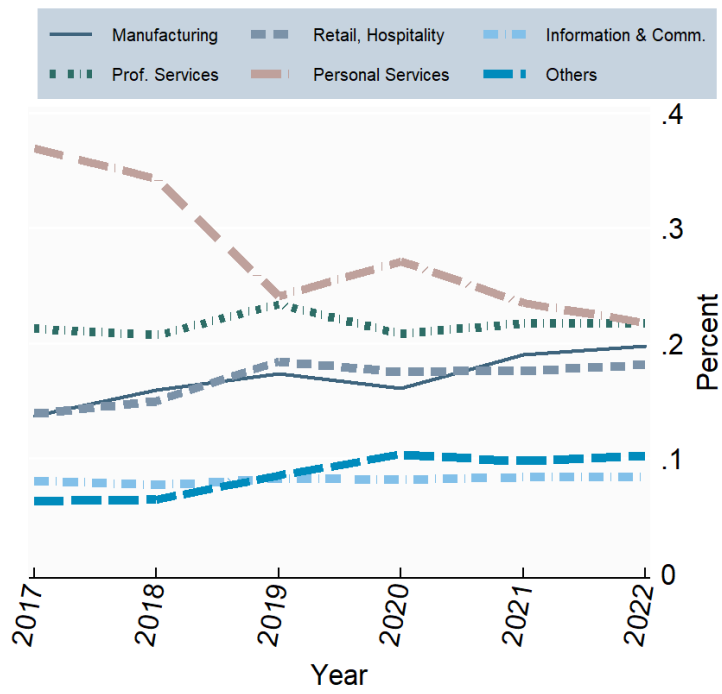


Figure 9: Industry Composition of Online Job Vacancies year, 2017 - 2021