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Do Economic Crises Reshape the Skill Content of Jobs? Evidence from Organizational Changes in the Post-Pandemic Era[†]

Niklas Benner[‡] Felix Heuer[§] Rebecca Kamb[¶] Eduard Storm[‖]

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Abstract

How do economic crises reshape firms' skill demand through changes in the organization of work? Using the COVID-19 pandemic as a shock to workplace practices, this paper examines whether short-term disruptions prompt lasting shifts in job requirements. We draw on 11 million German online job vacancies from 2017–2024 and implement an event-study design that exploits pre-pandemic variation in work-from-home feasibility across occupations. This approach identifies firms' differential exposure to remote-work constraints based on the occupational mix of their job postings. We find that crisis-induced shifts in skill demand were mainly short-lived, but one adjustment persisted: a lasting rise in interactive requirements, reflecting the emergence of hybrid collaboration. This form of organizational change contrasts with the technology-driven automation emphasized in prior crises and was shaped mainly by structural factors —digital infrastructure, firm size, and sectoral exposure —rather than by cyclical variation. Our results show that temporary shocks can trigger selective and enduring shifts in firms' skill demand through evolving workplace organization.

Keywords: Online Job Ads, Skill Demand, Work-from-Home Feasibility, COVID-19, Task Reallocation, Event Study
JEL Codes: J23, J24, J63, O33

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1 Introduction

Technological change has long been recognized as a central force reshaping labor demand, traditionally viewed as a gradual process of routine-biased technological change (RBTC) that reallocates work from routine to non-routine tasks (Acemoglu & Autor 2011; Autor, Levy & Murnane 2003; Goos, Manning & Salomons 2014). Recent research shows that crises can act as accelerators of such processes (Jaimovich & Siu 2020). During the Great Recession 2007/08, for example, firms raised education and experience requirements —a phenomenon termed “upskilling” (Modestino, Shoag & Ballance 2019). While some of these adjustments were cyclical, others generated persistent shifts in the composition of jobs, consistent with ongoing RBTC (Blair & Deming 2020; Hershbein & Kahn 2018).

This paper argues that the COVID-19 pandemic provides a different mechanism for adjustment. Earlier crises amplified technology-based automation as firms sought to substitute away from routine routine tasks. COVID, in turn, imposed organizational constraints as lockdowns forced firms to reorganize production around the feasibility of performing tasks remotely. Many firms invested heavily in digital tools (Barth, Bryson & Dale-Olsen 2022; Gathmann, Kagerl, Pohlan & Roth 2024), but these investments primarily sought to preserve rather than replace (or augment) labor by enabling remote collaboration (Arntz, Böhm, Graetz, Gregory, Lehmer & Lipowski 2024). Whether such reorganization merely reflected temporary disruption or induced lasting changes in skill demand remains an open question.

We address this question by analyzing how firms adjusted the skill content of jobs in response to COVID-19. Using more than 11 million German online job vacancies from 2017–2024, we estimate a dynamic event-study that exploits pre-pandemic differences in work-from-home (WFH) feasibility across occupations. Because all firms were affected by lockdowns, we adopt a continuous-treatment approach in which exposure varies with each firm’s occupational mix (Callaway, Goodman-Bacon & Sant’Anna 2024). Conditioning on firm, region, and broad occupation fixed effects permits comparisons of vacancies within firms but across jobs with differential WFH feasibility (such as cashiers versus retail managers).

This research design allows us to not only study skill shifts *within* occupations, but also to distinguish pandemic-specific (cyclical) responses from post-pandemic (persistent) shifts.

Our findings indicate that most pandemic-induced changes in skill demand were short-lived, typically fading within one to three years. Nevertheless, some adjustments persisted as firms institutionalized hybrid work practices. Classifying advertised requirements into five skill groups —non-routine (NR) cognitive, NR interactive, routine cognitive, routine manual, and NR manual —we find a lasting increase in demand for interactive skills until mid-2024, consistent with the consolidation of hybrid collaboration in modern workplaces. We also find a temporary but less pronounced increase in demand for cognitive skills. As expected, we also find a persistent decline in demand for manual skills, reflecting a de-emphasis of physical activities in job postings. Our results suggest *upskilling within occupations* in terms of growing demand for social skills (Deming 2017) rather than previously emphasized cognitive skills (Hershbein & Kahn 2018).

To interpret these patterns, we extend the canonical Acemoglu & Autor (2011) framework by introducing task-specific constraints that penalize in-person tasks. In our framework, firms re-optimize task allocation by shifting work away from remote-incompatible (manual) to remote-compatible (NR cognitive, certain routine cognitive and interactive) domains.

Combining our vacancy data with firm-registry information, regional, and EU KLEMS–INTANProd industry data, we then contrast structural with cyclical drivers for our observed upskilling phenomenon and document three main results. First, firms geared their job postings stronger towards cognitive- and interactive-intensive occupations, revealing even more pronounced and persistent upskilling. Second, the lasting increase in interactive skill demand is strongest among firms operating in industries with richer digital infrastructure —especially communication technology within business services. This finding highlights that hybrid collaboration took hold where technological and organizational preconditions were already favorable. Third, unlike U.S. evidence, we find no link between regional unemployment fluctuations and upskilling. This observation is consistent with Germany's short-time work scheme, an institutional feature that limits increases in unemployment during recessionary periods and thereby mutes the expansion of potential applicants that typically underlies cyclical upskilling channels. Combined, our findings suggest that structural rather than cyclical drivers shaped pandemic-induced changes in skill demand.

Our study contributes to two strands of the literature. First, we extend research on "recessions and recruitment" by showing that crises can reshape skill demand through organizational change rather than purely through technological change, which we conceptualize through task-specific constraints. Earlier work has instead emphasized routine-biased technological change as a key channel and captured upskilling with formal hiring standards or narrow sets of cognitive skills in the aftermath of the Great Recession 2007/08 (Hershbein & Kahn 2018; Modestino, Shoag & Ballance 2019).[1] Importantly, our results suggest that central insights from the US-dominated upskilling literature may not translate to the European context, where institutional features such as short-time work schemes dampened cyclical adjustment channels. This scheme was particularly pronounced in Germany (Brinkmann, Jäger, Kuhn, Saidi & Wolter 2024; Kagerl 2024) but was also implemented widely across EU economies (Drahokoupil & Müller 2021).[2]

Second, we extend insights on the labor market consequences of COVID-19 by emphasizing WFH feasibility as a central driver of firms' skill shifts. Many studies have documented the persistence of remote work[3], especially through pandemic-driven investments into digital collaboration technologies.[4] These investments boosted firms' resilience (Bai, Brynjolfsson,

[1]Related, Beaudry, Green & Sand (2016) show that job requirements shifted after the Dotcom Bubble and through the Great Recession, with a reversal in rising demand for cognitive tasks. Modestino, Shoag & Ballance (2016) find similar patterns for US local labor markets where unemployment varied in the aftermath of the Great Recession. More broadly, recessions have been shown to accelerate polarization (Jaimovich & Siu 2020) or mismatches (Şahin, Song, Topa & Violante 2014). Others show long-run effects on formal requirements (Blair & Deming 2020; Modestino, Burke, Sadighi, Sederberg, Stern & Taska 2023), and, more recently, COVID-induced implications on IT skills (Oikonomou *et al.* 2023; Soh *et al.* 2024) and task adjustments more broadly (Blanas & Oikonomou 2023; Gu & Zhong 2023).

[2]Consistent with the view that short-time work mutes cleansing effects during recessions, Meriküll & Paulus (2024) show that job retention schemes during COVID came with weaker worker reallocation.

[3]See, e.g., Adrjan, Ciminelli, Judes, Koelle, Schwellnus & Sinclair (2025), Buckman, Barrero, Bloom & Davis (2025), Gill, Hensvik & Nordström Skans (2025), Hansen, Lambert, Bloom, Davis, Sadun & Taska (2023), Kagerl & Starzetz (2023), and Krause, Trumpp, Dichtl, Kiese & Rutsch (2024).

[4]See Arntz, Böhm, Graetz, Gregory, Lehmer & Lipowski (2024), Barth, Bryson & Dale-Olsen (2022), and

Jin, Steffen & Wan 2021; Oikonomou, Pierri & Timmer 2023), shifted their labor demand toward remote-compatible jobs (Bratti, Brunetti, Corvasce, Maida & Ricci 2024), and induced them to reorganize work and commuting practices (Coskun, Dauth, Gartner, Stops & Weber 2024). Our main contribution is to show which skill adjustments existed, persisted, and what factors drove them. In this sense, our paper echoes the documented *"WFH stickiness"* (Barrero, Bloom & Davis 2021) – but adds new insights on *where it sticks*.

By showing how an organizational shock redefines the boundaries of work, our paper contributes to ongoing debates on structural transformation in advanced economies. Temporary disruptions, as we show, can prompt persistent reallocation of labor even in the absence of new automation technologies.

The remainder of the paper proceeds as follows. Section 2 outlines the conceptual background that guides our empirical analysis. Section 3 describes the data and construction of key measures. Section 4 presents the empirical strategy, whose results and robustness tests are shows in section 5. Section 6 discusses mechanisms. Finally, section 7 concludes.

2 Conceptual Background

2.1 Task-based framework and the role of Remote Work

The pandemic confronted firms with *organizational* rather than purely technological change: production could continue only insofar as tasks could be coordinated remotely. To better understand how such constraints affect the allocation of work, we extend the canonical task-based framework by Acemoglu & Autor (2011) by including a task-specific WFH feasibility parameter that captures how the pandemic altered effective productivity across skill groups. This approach is supported by micro evidence that productivity under WFH varies systematically across workers and occupations (Burdett, Etheridge, Tang & Wang 2024; Shen 2023).

Gathmann, Kagerl, Pohlan & Roth (2024). Relatedly, others have highlighted the role of digital infrastructure for local labor markets Ben Yahmed, Berlingieri & Brüll (2024).

We sketch the logic from the model below and refer to Appendix C for details.[5]

Canonical task-based framework. In the canonical model, occupations are conceived as bundles of tasks, and firms allocate workers to tasks according to their comparative advantages. Each task i can be carried out by low-skill ($l(i)$), medium-skill ($m(i)$), or high-skill ($h(i)$) workers, with task-specific productivities $\alpha_j(i)$ for skill groups $j \in \{L, M, H\}$ and factor-augmenting technologies A_j. The production function for task i is then given by $y(i) = A_L\alpha_L(i)l(i) + A_M\alpha_M(i)m(i) + A_H\alpha_H(i)h(i)$.[6]

Because comparative advantage schedules $\alpha_j(i)$ differ across skill groups, the task space is partitioned into three intervals: $[0, I_L]$, $[I_L, I_H]$, and $[I_H, 1]$, allocated to low-, medium-, and high-skill workers, respectively. The thresholds I_L and I_H are determined by no-arbitrage conditions ensuring the cost of performing the marginal task is equal across adjacent groups:

$$A_L\alpha_L(I_L)\,\frac{L}{I_L} = A_M\alpha_M(I_L)\,\frac{M}{I_H - I_L}, \tag{1a}$$

$$A_M\alpha_M(I_H)\,\frac{M}{I_H - I_L} = A_H\alpha_H(I_H)\,\frac{H}{1 - I_H}. \tag{1b}$$

Extension: Remote-work constraints. We interpret the COVID-19 pandemic as an exogenous shock to task allocation, driven by restrictions on physical presence. We model these circumstances as a task-specific constraint that became binding during the pandemic: the feasibility of remote work. Let $\psi_j(i) \in [0, 1]$ denote the degree to which task i can be performed remotely (similar to Adams-Prassl, Boneva, Golin & Rauh (2022) and Dingel & Neiman (2020)). Effective productivity then becomes:

$$\tilde{A}_j(i) = A_j\alpha_j(i)\,\boldsymbol{\psi_j(i)}. \tag{2}$$

A high $\psi_j(i)$ value indicates that a task can be carried out remotely with little productiv-

[5]See Acemoglu, Kong & Restrepo (2025) for an overview of recent advances in the task-based framework.

[6]Unlike the canonical model, we omit potential substitution of labor by capital to keep the exposition centered around the relevant margins of adjustment for our purposes.

ity loss (e.g. data analysis), whereas a low $\psi_j(i)$ captures high penalties for tasks requiring on-site presence (e.g. machinery repair).

Comparative statics under a binding constraint. Substituting $\tilde{A}_j(i)$ from (2) into the no-arbitrage conditions (1), and log-differentiating with respect to WFH feasibility $\psi_j(i)$ while holding A_j, $\alpha_j(i)$, and (L, M, H) constant, yields the following closed-form solutions:

$$\Delta I_L = I_L(1 - I_L)\, r_L \;+\; I_L(1 - I_H)\, r_H, \tag{3a}$$

$$\Delta I_H = (1 - I_H) I_H\, r_H \;+\; (1 - I_H) I_L\, r_L, \tag{3b}$$

where $r_L \equiv \Delta \ln\big(\frac{\psi_L}{\psi_M}\big)\big|_{I_L}$ and $r_H \equiv \Delta \ln\big(\frac{\psi_M}{\psi_H}\big)\big|_{I_H}$. Intuitively, when $\psi_j(i) < 1$, remote-work constraints bind and penalize the least remote-feasible tasks. We assume $\psi_H(i) > \psi_M(i) > \psi_L(i)$, so tasks usually performed by high-skill workers are more compatible with remote work than those performed by lesser-skilled workers. In this case, both I_L and I_H shift downward, such that the low-skill domain contracts and the high-skill domain expands. The net effect on the medium-skill domain is ambiguous depending on the size of both shifts.

This mechanism is qualitatively distinct from routine-biased technological change. RBTC assumes new technologies automate certain tasks, thereby displacing labor. In contrast, remote-work constraints operate through organizational reallocation by complementing remote-compatible activities while constraining those requiring physical proximity (Gu & Zhong 2023). We thus interpret occupational WFH feasibility as a central determinant of firms' adjustment margins during the pandemic (Bai, Brynjolfsson, Jin, Steffen & Wan 2021).

From theory to empirics. To test the implications of our extension empirically, we map the three theoretical domains (low, medium, high) into five well-established skill groups: (i) non-routine (NR) cognitive, (ii) NR interactive, (iii) routine (R) cognitive, (iv) R manual, and (v) NR manual. Figure A1 validates this mapping using data from the IAB Occupation Panel (Grienberger, Janser & Lehmer 2023). We find a clear three-domain pattern: earnings are hightest in NR cognitive occupations (160 EUR per day), followed by NR interactive and R cognitive occupations (110 EUR per day and 100 EUR per day), and, lastly, manual occupations (75-90 EUR). Educational attainment follows the same structure, with tertiary degrees concentrated in NR cognitive occupations (60 %), followed by NR interactive (33 %) and R cognitive (16 %) occupations, but nearly absent among manual occupations (< 5 %).

2.2 Hypotheses

Our empirical analysis uses job postings, which describe required *skills* rather than *tasks*. Following Acemoglu & Autor (2011), we interpret skills as endowments workers use to perform tasks and treat vacancy requirements as proxies for the underlying task content. We use the term "skill demand" while remaining conceptually grounded in the task-based model.

Short-term: 2020-2022 During the acute phase of the pandemic, lockdowns imposed binding constraints on in-person work. These adjustments were shaped by the extent to which tasks could be performed remotely, giving rise to the following hypotheses:

Hypothesis 1: Increase in (non-routine) cognitive skills

When medium-skill workers face stronger remote-work penalties than high-skill workers (ψ_M/ψ_H falls), the upper cutoff I_H shifts downward and the high-skill domain expands.

Hypothesis 2: Decline in manual skills

When low-skill workers face stronger penalties than medium-skill workers (ψ_L/ψ_M falls), the lower cutoff I_L shifts downward and the low-skill domain contracts.

Hypothesis 3: Ambiguous effects on interactive and routine cognitive skills

Interactive and routine-cognitive tasks occupy the middle domain, affected by both shifts. Their response is thus theoretically ambiguous.

Long-term: 2023-2024 After restrictions were lifted, remote collaboration persisted as an integral part of work organization (Adrjan, Ciminelli, Judes, Koelle, Schwellnus & Sinclair 2025; Barrero, Bloom & Davis 2021). Pandemic-era investments in digital infrastructure and new managerial practices increased effective productivity for remote tasks (increase in $\psi_H(i)$) and relaxed the constraint for high-skill groups, summarized in our final hypothesis:

Hypothesis 4: Lasting upskilling in WFH-feasible jobs

Organizational and technological adaptation made remote collaboration sustainable. Some reallocation toward remote-compatible tasks thus became "locked in", generating a persistent rise in cognitive and interactive skill demand in WFH-feasible jobs.

3 Data

We next describe the data and construction of our key variables, which allow us to test our hypotheses empirically.

Primary Data: Online Job Vacancies. Our primary data consists of German online job vacancies between 2017 and 2024, collected by Palturai GmbH and its subsidiary Finbot. The data cover the universe of online job ads for professionals published in Germany, comprising job boards, company websites, and temporary employment platforms – similar in scope to other commercial sources such as Lightcast or Indeed.

While the analysis of job postings has become increasingly popular in economic research (Kircher 2022), our OJV data offer several unique strengths that enhance data quality. First, we have access to the full original vacancy texts, which allows us to maintain transparency over the raw data and develop our own text-based taxonomies tailored to our research design. Second, we partition each vacancy into distinct text segments based on their functional purpose ("zoning"), which improves precision in identifying job requirements from relevant text sections.[7] Appendix OA.1 summarizes key steps in our data preparation, including our segmentation, deduplication, and external validity procedures.

[7] An ideal vacancy typically consists of four parts: i) firm description, introducing the employer; ii) task description, describing the role and responsibilities; iii) skill requirements; and iv) benefits and perks associated with the position. For our skill outcomes, we focus on the task and skill segments, which directly reflect job content. For our WFH measure, we focus on the benefits section, which usually advertises remote work options.

For our analysis, we use more than 10 million vacancies. We only use vacancies advertising regular work, thereby removing vacancies seeking apprenticeships, trainees, and other types of irregular work. To ensure high data quality and maintain comparability with administrative data, we further remove vacancies (i) posted by temporary employment agencies, (ii) with missing information on key variables (date, location, occupations), and (iii) from firms that did not post vacancies between 2018 and 2022, to avoid compositional shifts due to firm entry and exit. Appendix OA.2 provides further details on these sample restrictions.

A common concern with vacancy data is representativeness. In Appendix OA.3 we show that our postings indeed primarily reflect larger, well-established firms in metropolitan labor markets, consistent with where most professional hiring occurs. To bolster the external validity of our analysis, we provide two pieces of supporting evidence. First, we show in Appendix OA.3 that aggregate vacancy trends in our data closely mirror those reported by the (representative) IAB Job Vacancy Survey (Bossler, Gürtzgen, Kubis, Küfner & Popp 2021). Second, we present re-weighting analyses in section 5.2 to demonstrate the robustness of our baseline results across distinct weighing schemes.

Secondary Data: Commercial Register, Regional Data & EU KLEMS. We enrich our vacancy-level data with firm-, regional-, and industry-level data from several external sources. First, we link job postings to the German Commercial Register, obtained from Palturai/Finbot, based on firm identifiers. This linkage is feasible for 60 % of postings and provides information on firm age, size brackets, and 5-digit industry codes (WZ08), allowing us to characterize firms that were the driving force of observed changes in skill demand. Second, we merge county-level indicators on skill composition, demographic structure, industrial mix, and unemployment rates to capture local economic conditions that may shape recruitment responses to COVID-19. These data come from the official regional statistics database maintained by the Federal Statistical Office and the statistical offices of the German federal states.[8] Finally, we draw on industry-level indicators from EU KLEMS & INTANProd to capture sectoral differences in digital infrastructure (Bontadini, Corrado, Haskel, Iommi & Jona-Lasinio 2023).[9] This dataset combines productivity accounts with information on intangible assets such as software, databases, and digital capital. We use capital-stock measures at the NACE2 level to proxy pre-pandemic differences in information and communication technologies.

Skill Taxonomy from BERUFENET. Building on the conceptual mapping in Section 2, we operationalize the five skill groups using job descriptions from BERUFENET. This online platform is provided by the Federal Employment Agency and conceptually similar to O*NET (US) and ESCO (EU). We process the raw BERUFENET information through a multi-step procedure to produce a standardized dictionary of about 9,500 unique keywords suitable for text extraction (see Appendix OA.4 for details).

Figure A2 illustrates the most frequent keywords within each of the five skill groups, showing that the classification aligns well with established typologies of job contents (see Storm (2023) for an overview). For each vacancy i and skill group j, we then compute the share of extracted skill keywords belonging to group j:

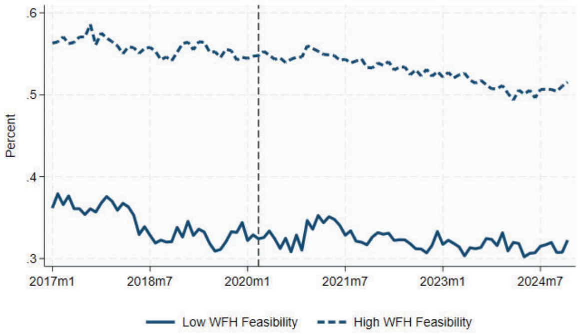
$$S_{ij} = \frac{\text{Number of skill keywords from group } j \text{ in vacancy } i}{\text{Total number of skill keywords in vacancy } i}. \tag{4}$$

By construction, this definition implies (i) $S_{ij} \in [0,1]$ and (ii) $\sum_J S_{ij} = 1$.[10] These *relative* skill measures reflect our outcome measures and, unlike absolute skill measures, mitigate concerns about variation in posting length or job-specific jargon, thus enabling meaningful comparisons across occupations and over time.

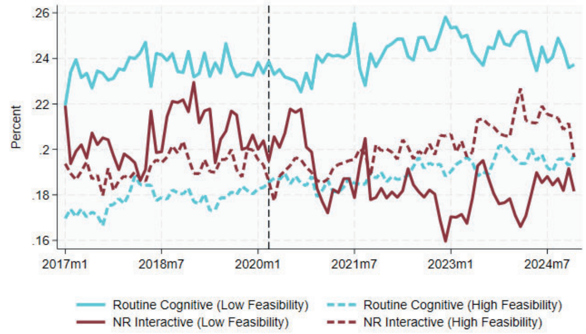
[8]The data cover a broad range of county-level indicators, including local skill composition, demographic structure (e.g., age, gender, citizenship), industry mix, and unemployment rates. These regional statistics can be downloaded free of charge from: https://www.regionalstatistik.de/genesis/online/

[9]The data can be downloaded free of charge: https://euklems-intanprod-llee.luiss.it/download/

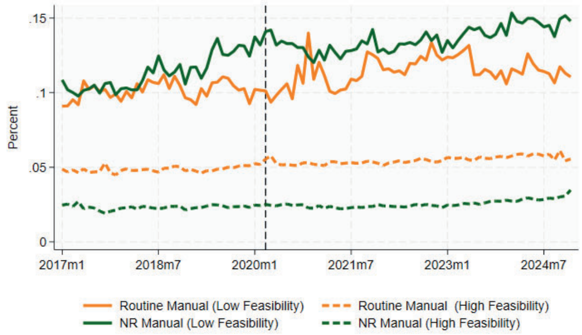
[10]Variations of this measure have been widely used in the task literature, making our results comparable to previous research (Antonczyk, Fitzenberger & Leuschner 2009; Gathmann & Schönberg 2010; Spitz–Oener 2006; Storm 2022; Storm 2023).



(a) Non-Routine Cognitive



(b) Non-Routine Interactive, Routine Cognitive



(c) Non-Routine Manual, Routine Manual

Figure 1: Skill Demand in Online Job Vacancies by WFH Feasibility: 2017–2024

NOTE. — We define high vs. low feasibility based on the median of our pre-pandemic WFH measure. The vertical dashed line indicates March 2020, the onset of the first lockdown. Source: Palturai GmbH/Finbot AG (OJV data), BERUFENET (skill requirements), own calculations.

Figure 1 displays the average composition of skill requirements for high- and low-WFH occupations between 2017 and 2024, with two emerging insights. First, level differences between high- and low-WFH occupations align closely with theoretical predictions. High-WFH occupations have a stronger emphasis on NR cognitive skills (50-60 % of all requirements), compared to low-WFH occupations (30-40%). In contrast, low-WFH occupations are much more manual-intensive (20-25 %) than high-WFH ones ($<$ 10%). Similarly, low-WFH occupations are more routine-cognitive-intensive (22-25 %) than high-WFH ones (17-20 %), though overall more balanced. These differences are persistent over time, underscoring the link between remote feasibility and task composition.[11]

[11]While our focus is on differences by WFH feasibility, it is worth noting that demand for NR cognitive skills has declined for both high- and low-WFH occupations, falling from around 50% of postings in 2017 to

Second, the pandemic reinforced some of the divides in skill demand. Especially interactive skill demand increased in high-WFH occupations (from 19% in 2019 to 22% in 2024), but fell in low-WFH occupations (from 20% to 18%). This divergence points to a reallocation toward remote-compatible forms of interaction in jobs with the necessary digital infrastructure, at the expense of face-to-face tasks tied to on-site presence. Manual skill demand, in turn, remained very low in high-WFH jobs but increased somewhat in low-WFH ones, where substitution away from on-site activities seems limited.

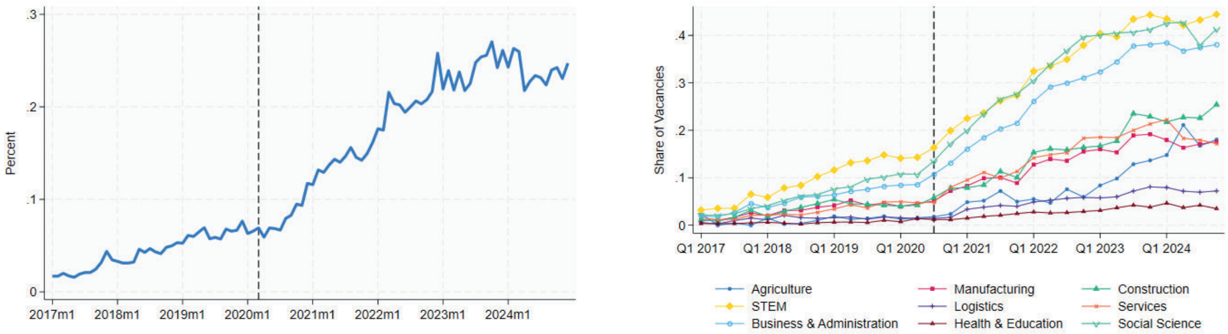
Taken together, the descriptive insights confirm the cognitive–manual dichotomy implied by our theoretical framework, while revealing nuanced dynamics for interactive and routine-cognitive skills. Next, we test these mechanisms formally in our empirical analysis.

4 Research Design and Empirical Strategy

Motivation and Treatment Definition. We exploit the COVID-19 pandemic as a natural experiment in work reorganization, treating the outbreak as an exogenous shock to firms' ability to perform tasks on-site. To that end, we compare changes in the skill composition of vacancies across occupations that differ in their suitability for remote work (conceptualized by the parameter ψ in Section 2).

We define a continuous treatment variable WFH_o capturing the share of pre-pandemic postings in occupation o (2017–2019) that explicitly offered remote work. This measure reflects structural differences in the technical feasibility of remote work and thus the scope for task reallocation under social-distancing constraints. Importantly, the predetermined treatment also ensures that our identifying variation is not contaminated by pandemic-era

around 40% in 2024. This observation might be surprising, considering the vast literature pointing to rising skill requirements in recent decades (see Woessmann (2024) for a recent overview). Consistent with our stylized facts, however, demand for cognitive tasks and returns to associated skills have generally decreased since the 2000s (Beaudry, Green & Sand 2016; Castex & Kogan Dechter 2014; Frisvold & Kim 2024). Next to conceptual reasons, we cannot rule out mechanical reasons – such as certain skills becoming implicit over time (e.g., proficiency with MS office tools) – and compositional changes in our data. We explore these issues further in Appendix OA.3, alongside validation checks against external skill indicators from the IAB Occupational Panel, which also builds on BERUFENET data (Grienberger, Janser & Lehmer 2023).



(a) Overall

(b) By Major Occupational Group

Figure 2: Work-From-Home Offerings in Online Job Vacancies, 2017–2024

NOTE. — Panel 2a shows the overall share of vacancies explicitly offering work-from-home (WFH) options from 2017 to 2024. Panel 2b disaggregates the share of WFH offerings by broad occupational groups (1-digit, KldB 2010). Source: Palturai GmbH/Finbot AG (OJV data), own calculations.

outcomes that would otherwise give rise to reverse causality.

To identify WFH options, we extract references to remote work from the benefits section of job postings (see Figure A3 for a word cloud).[12] Figure 2 shows the share of vacancies explicitly offering WFH surged after early 2020 – from below 5% in 2017 to over 25% by 2023 – and has since stabilized at elevated levels. Reassuringly, advertised WFH options also vary strongly across occupations. The post-pandemic increase in WFH options is concentrated in high-WFH occupations (STEM, business, social sciences), rather than low-WFH occupations (health, education, and logistics).[13]

Treatment Validation. We benchmark our vacancy-based WFH_o against two external indicators: (i) the Home Office Potential (HOP) index by Bruns, Matthes & Stops (2025), based on formal work conditions stated in BERUFENET, and (ii) survey-based occupational measures of WFH feasibility from Alipour, Falck & Schüller (2023). Figure A4 shows that both correlate strongly with our measure ($\rho > 0.7$). At the aggregate level, our monthly WFH trend also closely mirrors data from the Indeed Hiring Lab ($\rho = 0.98$), reinforcing the

[12]By extracting WFH options from the benefits section, we avoid false positives if terms appear in another context (e.g., maintaining infrastructure to support remote work as part of the advertised job).

[13]Similarly, the share of workers who can perform tasks remotely has increased the most in occupations with a high pre-existing share of WFH-feasible tasks (Adams-Prassl, Boneva, Golin & Rauh 2022).

external validity of our treatment variable (Figure A5).

Event-Study Framework. We estimate an event-study model with continuous treatment intensity from Q1 2017 to Q4 2024, exploiting variation in pre-pandemic WFH feasibility across detailed occupations. We define occupations based on the German classification of occupations (KldB2010 v2020), by combining (144) 3-digit KldB codes with their complexity level (5th digit), resulting in 328 detailed occupational groups.[14] Our model is estimated at the vacancy level, where the interaction of pre-pandemic WFH feasibility with time indicators captures differential dynamics across occupations:

$$\begin{aligned} S_{ijto} = \eta WFH_o + \sum_{m=-37,\, m\neq -1}^{46} \beta_m \left(WFH_o \times 1\{t = m\} \right) \\ + X'_{rt}\lambda + Z'_{ijto}\theta + \gamma_{jt} + \gamma_k + \kappa_s + \phi_q + \epsilon_{ijto} \end{aligned} \tag{5}$$

The outcome S_{ijto} measures the relative share of skill group j (NR cognitive, NR interactive, routine cognitive, routine manual, NR manual) in vacancy i posted by firm j for occupation o at time t. The pre-pandemic treatment variable WFH_o captures exogenous variation in occupations' remote-work feasibility. All key variables are multiplied by 100 to permit an interpretation in percentage point changes (treatment) and responses (outcome).

We include three groups of controls: (i) region-level covariates X_{rt} (e.g., workforce composition), (ii) job-specific characteristics Z_{ijto} (education, experience), and (iii) a rich set of fixed effects (FE). We include firm FE and firm-specific linear time trends (γ_{jt}) to account for unobserved firm heterogeneity, 2-digit occupation FE (γ_k) to absorb differences in baseline skill demand, state FE (κ_s) to account for differential regional policies and COVID exposure, and (iv) job board/source FE (ϕ_q) to abstract from compositional changes across posting

[14] The job complexity measures distinguish between helpers, professionals, specialists, and expert workers within the same occupation. For our analysis we combine specialist- and expert-level jobs into a single highly-skilled category because they perform similar sets of tasks and exhibit similar pre-pandemic WFH feasibility. In contrast, helpers and professionals differ more strongly in terms of the underlying task space and remote-feasibility.

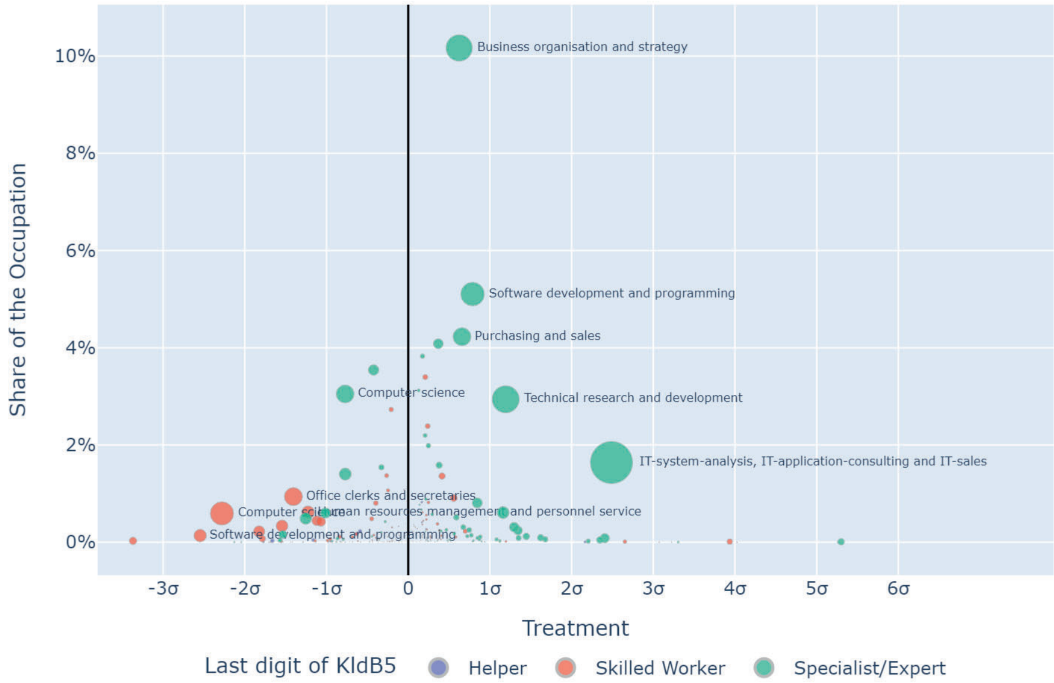


Figure 3: Treatment Variation: Work-from-Home Feasibility, 2017–2019

NOTE. — Each circle represents one detailed 3-digit occupation as defined in section 4. The x-axis shows the residualized WFH share per occupation. The y-axis shows the share of total job postings for each occupation. Source: Palturai GmbH/Finbot AG (OJV data), own calculations.

platforms.[15] Standard errors are clustered at the detailed 3-digit occupational level.

Identification comes from within-firm comparisons of vacancies with different WFH feasibility but similar broader occupational structure. Figure 3 visualizes this variation by plotting the standardized treatment intensity against each occupation's share in advertised jobs. Our identifying variation is mainly based on a diverse set of occupations in business organization, retail-oriented, and technical or IT-related fields. Much of this variation also reflects differences in job complexity within the same occupational domain.

The dynamic structure allows us to separate temporary from persistent shifts. While η captures level differences in WFH feasibility, the main coefficients of interest, β_m, trace dynamic responses in skill demand across high- and low-WFH occupations relative to Q4

[15]By including firm FE and firm-specific linear time trends, we account for latent and time-varying firm characteristics such as changing norms towards remote work. Well-managed firms, for example, adopt WFH-enabling technologies more often, suggesting managerial attitudes toward remote work contribute to variation in WFH arrangements (Kambayashi & Ohyama 2025).

2019 ($t = -1$). An estimate $\beta_m > 0$ implies stronger relative shifts in high-WFH jobs, whereas $\beta_m < 0$ implies stronger shifts in low-WFH jobs. Based on our theoretical framework (Section 2), we expect: (i) $\beta_m > 0$ for NR cognitive skills, (ii) $\beta_m < 0$ for manual skills, and (iii) $\beta_m \gtrless 0$ for interactive and routine cognitive skills, reflecting short-run task reallocation under binding constraints during 2020–22; and (iv) persistent $\beta_m > 0$ for cognitive and interactive skills after 2023, in line with lasting organizational adaptation to remote work.

5 Main Results

5.1 Baseline Findings

We begin by estimating how firms' skill demand evolved in response to the COVID-19 shock, conditional on pre-pandemic WFH feasibility. Figure 4 plots the estimated interaction effects (β_m) relative to the fourth quarter of 2019. Among all skill groups, the most persistent and economically meaningful shifts arise for interactive skills, consistent with the emergence of hybrid collaboration.

I. Short-term responses: 2020–2022 (H1-H3)

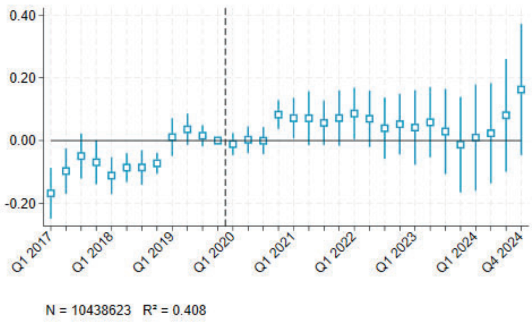
H1: NR Cognitive skills. Consistent with our first hypothesis, we find evidence that aligns with the predicted expansion of high-skill tasks when medium-skill workers face stronger remote-work penalties (ψ_M/ψ_H falls). A 1 pp. increase in WFH feasibility is associated with a modest, short-lived rise in demand for NR cognitive skills around late 2020. The treatment effect peaks at around 0.1 pp. between 2020Q4-2021Q1, coinciding with the second lockdown period in Germany ("Lockdown light"). Since NR cognitive skills represent 40% of all stated requirements, our estimate implies an increase by 0.25%. From 2021 onward the estimates turn insignificant, suggesting a temporary reallocation rather than a lasting shift. Note that the pre-pandemic period already shows some upward movement, warranting caution in our interpretation (though the absence of pre-trends in 2019 supports an interpretation of crisis-related reallocation in skill demand).

H2: Manual skills. In line with our second hypothesis, we observe that higher WFH feasibility is associated with a decline in demand for manual skills. For routine manual skills, estimates turn negative from mid-2020 and reach about –0.1 pp. by 2022 (-1% relative to the mean). For non-routine manual skills, we find similar results, though the pre-existing downward trend points to a structural decline unrelated to the pandemic. Overall, these results support the theoretical prediction that when low-skill groups are penalized more strongly (ψ_L/ψ_M falls), the manual tasks domain contracts.

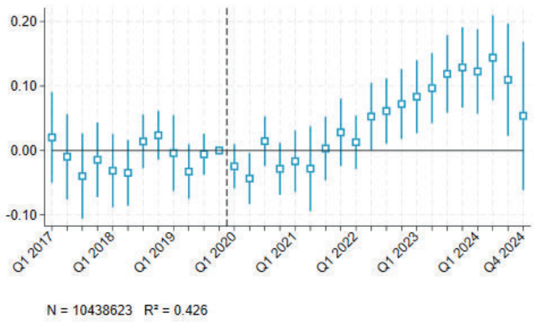
H3: Interactive and routine cognitive skills. The results for skills in the intermediate domain of the skill distribution are mixed, consistent with our third hypothesis. While we observe a brief decline for interactive skill demand during the acute crisis period, demand quickly rebounded, with no systematic differences through the end of 2022. In comparison, demand for routine cognitive skills displayed a modest uptick in early 2020, before turning insignificant. These dynamics reflect the ambiguity in our theoretical framework as outcomes depend on how I_L and I_H shift relative to each other.

II. Long-term responses: 2023–2024 (H4)

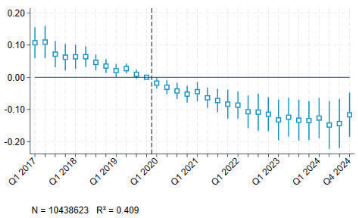
H4: Lasting upskilling in WFH-feasible jobs. Turning to long-run implications, we focus on dynamics from 2023 onward to assess whether shifts in skill demand persisted once immediate lockdown pressures had eased. Consistent with our fourth hypothesis, we find evidence consistent with a structural reallocation in high-WFH occupations. Most notably, demand for interactive skills displays sustained and statistically significant increases from early 2023 onward, with treatment effects peaking at around 0.2 pp. (1%), before fading by the end of 2024. Demand for (routine and non-routine cognitive) skills likewise remains



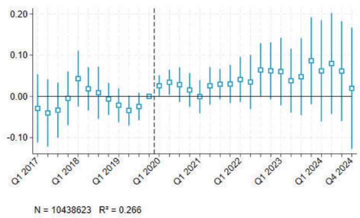
(a) Non-Routine Cognitive



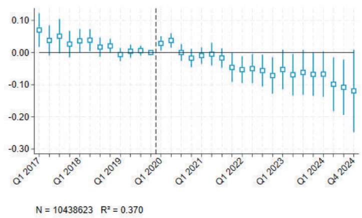
(b) Non-Routine Interactive



(c) Non-Routine Manual



(d) Routine Cognitive



(e) Routine Manual

Figure 4: Main Results: Event-Study Estimates of Skill Demand on Occupational WFH Feasibility, Q1 2017 – Q4 2024

NOTE. — The estimated coefficients are based on eq. 5 and reflect the estimated treatment effects $\hat{\beta_m}$ with 95% confidence interval and N = 10,438,623. All regressions include regional controls, job-specific controls on formal requirements, 2-digit occupation FE (KLDB 2010), firm FE, state FE, and source platform FE. Robust standard errors are clustered at the 3-digit+ occupation level as defined in section 4. Source: Palturai GmbH/Finbot AG (OJV data), BERUFENET (Skill terms), own calculations.

positively associated with WFH feasibility after 2021, though estimates are smaller and mostly imprecisely estimated. Combined, these findings indicate that at least part of the task reallocation induced by COVID became "locked in" once firms had reorganized around remote-compatible workplaces.

The persistence of our estimates highlights a mechanism in skill demand that is distinct from automation-driven task substitution (Blair & Deming 2020; Hershbein & Kahn 2018). Rather than replacing routine activities, firms adapted WFH technologies to organize work around digital collaboration tools and remote practices. The strongest and most robust results are on interactive skills, suggesting that the ability to collaborate, communicate, and coordinate effectively in virtual settings might have become a key source of comparative advantage, and resonates with the growing importance of social skills (Deming 2017).

5.2 Identification Threats & Robustness Tests

Our identification strategy assumes that, conditional on controls, variation in pre-pandemic WFH feasibility across occupations is exogenous to unobserved determinants of skill demand. Although we include a rich set of FE to absorb different dimensions of heterogeneity, potential threats remain. We therefore conduct a series of robustness checks that address (i) selection bias, (ii) alternative outcome definitions, (iii) model specification, and (iv) external validity of our WFH measure. Overall, these tests provide broad support for our main findings while adding nuance to their interpretation.

I. Selection Bias. We first address concerns that certain jobs were more likely to be advertised with remote work options even pre-pandemic. To mitigate systematic differences across occupations, we redefine our baseline continuous treatment as a binary treatment (as in Bai, Brynjolfsson, Jin, Steffen & Wan (2021)). We then apply entropy balancing (Hainmueller & Xu 2013) to make both groups comparable along key pre-pandemic characteristics, including firm size, firm age, and regional and industry-level measures (see Table A1).[16] The general patterns remain robust, though overall more muted (Figures A6 and A7). Notably, however, the pronounced increase in demand for interactive skills from mid-2022 onward remains robust to reweighting.

II. Outcome Definitions. Next, we contrast our baseline skill measure, capturing *relative* skill demand, with the *absolute* counts of required skills per job ad. This exercise addresses the concern that changes in relative shares may mechanically induce offsetting movements across skill groups, given that our baseline measure is exhaustive. Reassuringly, absolute counts provide similar insights such that we do not view our main findings an artifact of our outcome definition (Figure A8). In a complementary step, we test whether our findings

[16] We distinguish between "high WFH feasible" and "low WFH feasible" occupations using a 5% threshold of the pre-pandemic share of occupation-specific vacancies with WFH options. The binary specification allows us to implement entropy balancing more efficiently and ensures stable balancing weights even with high-dimensional covariates. In practice, the continuous treatment proved computationally infeasible due to memory constraints in the reweighting step.

are driven by specific keywords or clusters of related skills. To this end, we re-estimate our baseline model while excluding specific skill clusters based on semantic similarity using word embeddings derived from a German BERT model (Devlin *et al.* 2019).[17] Exclusion of skill clusters does not fundamentally change our results either, suggesting our results reflect broad shifts within skill groups (Figure A9).

III. Model Specification. We next vary key elements of our econometric specification. First, we replace firm-specific linear trends with standard firm FE, which removes the short-lived increase in demand for non-routine cognitive skills, but stabilizes pre-trends (Figure A11). Including linear firm trends appears to absorb part of the pre-pandemic variation and may thus slightly inflate our baseline results. For the remaining skill groups, our baseline results remain robust. Second, we include occupation FE at the fifth digit (rather than the second digit) to compare responses in skill demand within common job complexity levels. Although job complexity absorbs much of our identifying variation (because WFH feasibility is strongly correlated with job complexity), our main results remain markedly robust (Figure A10). Finally, we remove state FE to allow for differential impact of state-level differences in COVID-policies. This exercise also leaves our main results intact, such that COVID-policies are unlikely to drive our core findings (Figure A12). Overall, our main conclusions are not overly sensitive to model specification.

IV. External Validity of WFH Measure. Our vacancy-based measure of *actual* WFH use is constructed from job ads before the pandemic, when remote work was not yet widely accepted. In principle, it may thus capture differential technical feasibility *and* norms toward remote work. We address this concern by replicating our analysis with the “HOP indicator” – a *potential* WFH measure developed by Bruns, Matthes & Stops (2025). This measure is based on explicitly formulated working conditions from the job platform BERUFENET and is predetermined, hence less influenced by firms’ pre-pandemic policies. Despite differences in

[17] Examples of key clusters can be found in Table A2.

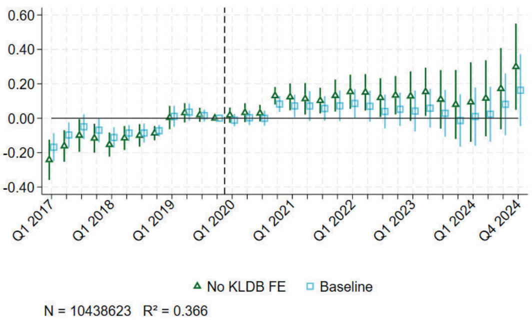
construction, this alternative WFH measure yields nearly identical insights to our vacancy-based measure (Figure A13). The close correspondence between our vacancy-based measure and the HOP indicator reinforces our view that the WFH treatment captures technological feasibility rather than changing norms towards remote work.

6 Compositional, Structural, and Cyclical Drivers

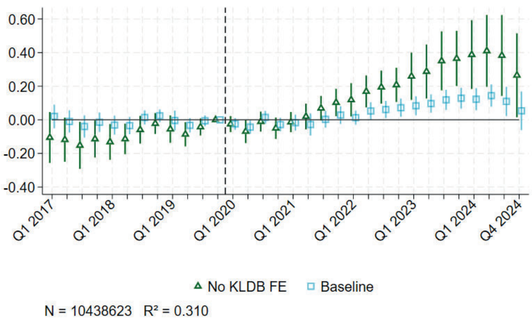
While our baseline results document broad, though mostly temporary, shifts in firms' skill demand, they remain silent on the forces underlying these dynamics. Did firms reorganize work within existing occupations by adjusting skill requirements, or did they change the composition of jobs they advertised? And to what extent were these adjustments shaped by structural or cyclical drivers? Disentangling these mechanisms is important, as it helps to clarify whether post-pandemic changes in skill demand primarily reflect (i) *compositional adjustments* in the types of jobs firms created, (ii) *structural differences* in firms' and industries' capacity to adapt to remote work, or (iii) *cyclical drivers* related to local labor market slack. In this section, we shed light on these channels.

Compositional Shifts: Within vs. Between Occupations. Our baseline specification exploits *within-occupation* variation by conditioning on 2-digit occupation FE, thereby focusing on changes in the relative skill content of jobs within narrowly defined occupations. This approach, however, abstracts from broader reallocation across occupations. To examine this margin, we re-estimate our model without occupation FE, thereby allowing for *between-occupation* changes in skill demand.

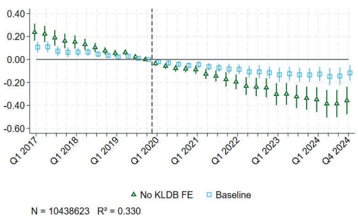
Figure 5 shows that omitting occupation FE leads to substantially stronger and more persistent upskilling. In response to a 1 pp. increase in WFH feasibility, demand for interactive skills rises by up to 0.4 pp. (2%), compared to 0.15 pp. (0.75%) in our baseline specification. Similarly, demand for both types of cognitive skills increases, though most notably for NR cognitive skills, where the treatment effect reaches about 0.3 pp. (0.75%), roughly



(a) Non-Routine Cognitive



(b) Non-Routine Interactive



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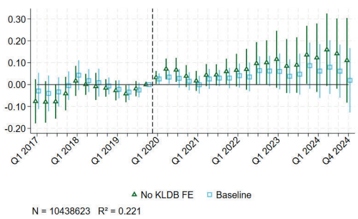
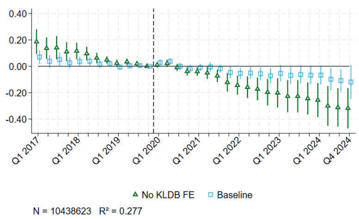


(d) Routine Cognitive



(e) Routine Manual

Figure 5: Event-Study Estimates of Skill Demand on Occupational WFH Feasibility (Within-Occupation versus Between-Occupation Comparison)

NOTE. — The estimated coefficients are based on a modified version of baseline eq. 5, which omits occupation fixed effects and thus exploits variation between occupations. Point estimates displayed with 95% confidence interval and N = 10,438,623. All regressions include regional controls, job-specific controls on formal requirements, firm FE, state FE, and source platform FE. Robust standard errors are clustered at the 3-digit+ occupation level as defined in section 4. Source: Palturai GmbH/Finbot AG (OJV data), BERUFENET (Skill terms), own calculations.

three times larger than in our baseline. These increases remain significant through the end of our observation period and are accompanied by a more pronounced decline in manual requirements. Taken together, these patterns point to a broader shift toward cognitively and socially intensive occupations. While within-occupation adjustments in task allocation were largely temporary, this between-occupation reallocation reflects a more persistent form of upskilling through expansion of higher-skilled jobs.

Firm Size and Digital Infrastructure. Firms' ability to reorganize work depends on structural characteristics such as size and digital infrastructure. Larger firms and those with advanced digital systems were better positioned to sustain operations during lockdowns and to integrate remote work technologies (Arntz, Böhm, Graetz, Gregory, Lehmer & Lipowski

2024; Gathmann, Kagerl, Pohlan & Roth 2024). In our framework, these characteristics mitigate the productivity penalties from remote work (ψ), which spaces task allocation across skill groups. To assess these structural drivers, we re-estimate equation (5) separately by firm size and by industry-level stocks of digital infrastructure.

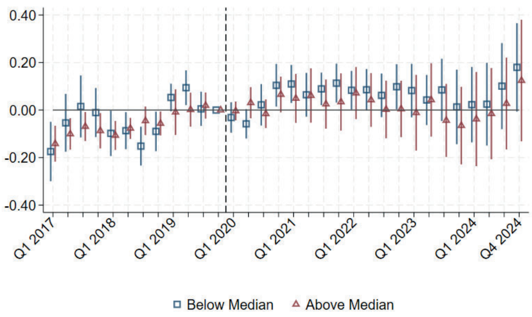
We classify firms as small or large based on the median number of employees in the German company registry and distinguish between industries with high versus low pre-pandemic IT and communication-technology (CT) capital using EU KLEMS & INTANProd data.[18] In both cases, we use pre-pandemic data to avoid concerns on reverse causality. The results (Figures 6–8) highlight three main insights.

First, the most pronounced and persistent pattern emerges for interactive skills, whose rising demand was driven by firms in high-IT industries (Figure 6) and – even more so – in high-CT industries (Figure 7). Firms operating in these industries had on average already developed the necessary infrastructure needed for virtual collaboration prior to the pandemic, which presumably facilitated the integration of hybrid work practices. In contrast, firms in low-CT industries did not increase their demand for interactive skills. The magnitude and persistence of these differential responses underline that digital infrastructure was central to organizational reconfiguration of work during the transition toward hybrid work practices.

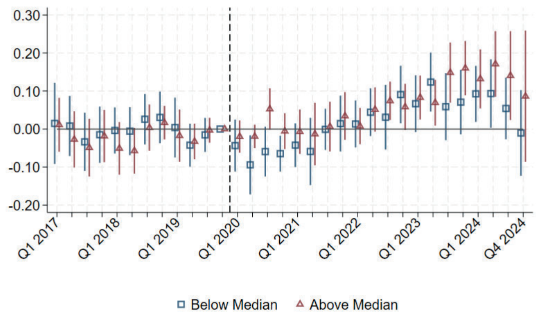
Second, the temporary increase in demand for NR cognitive skills during 2020–21 was concentrated among firms operating in low-CT industries (Figure 7). These firms may have faced stronger adjustment pressures during initial lockdowns as digital adoption during COVID mattered most in low-tech sectors (Bai, Brynjolfsson, Jin, Steffen & Wan 2021).

Third, firm size also mediated adjustments in skill demand, but less strongly than digital infrastructure. Smaller firms display somewhat stronger responses, though these differences are mostly insignificant. The clearest difference emerges for routine cognitive skills, where

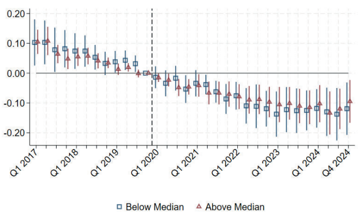
[18] Data from the EU KLEMS & INTANProd database combine productivity and intangible investment accounts. Data on German industries is currently available from 1995 - 2021. Specifically, we use data from the German capital accounts database, comprising information on the EUR value of software & database, information technologies, and collaboration technologies for 58 industries. See EUKLEMS & INTANProd (2021) for details and https://euklems-intanprod-llee.luiss.it/download/ for access.



(a) Non-Routine Cognitive



(b) Non-Routine Interactive



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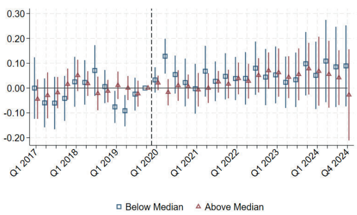
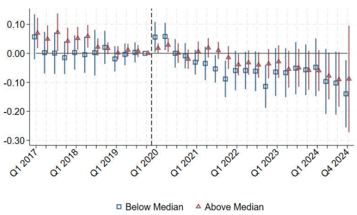


(d) Routine Cognitive



(e) Routine Manual

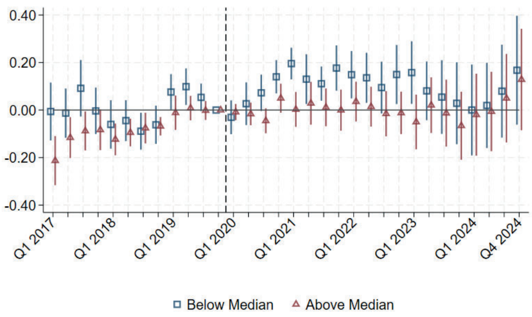
Figure 6: Event-Study Estimates of Skill Demand on Occupational WFH Feasibility (By IT Infrastructure)

NOTE. — The estimated coefficients are based on a modified version of baseline eq. 5,interacted with a binary variable equal to one for a firm operating in an industry with above-medium communication technology infrastructure. Point estimates displayed with 95% confidence interval and N = 10,438,623. All regressions include regional controls, job-specific controls on formal requirements, firm FE, (2-digit) occupation FE, state FE, and source platform FE. Robust standard errors are clustered at the 3-digit+ occupation level as defined in section 4. Source: Palturai GmbH/Finbot AG (OJV data), BERUFENET (Skill terms), own calculations.

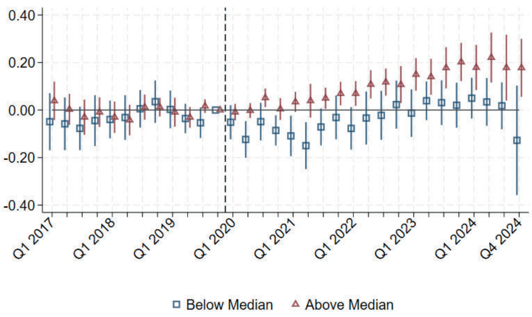
only smaller firms displayed a increase between early 2022 until mid 2024 (Figure 8).[19]

Overall, the results show that lasting changes in skill demand are concentrated in industries with high CT capital, where firms could integrate virtual collaboration more easily into hybrid work organization. The persistent rise in interactive skill demand in these industries points to a post-pandemic reorganization of work enabled by collaboration technologies, rather than IT–driven automation in the context of routine-biased technological change emphasized in prior research (Blair & Deming 2020; Hershbein & Kahn 2018).

[19]We have also explored other possible structural drivers, such as firm age. However, these analyses have not revealed meaningful insights, such that we have not included them in the paper. Results are available from the authors upon request.



(a) Non-Routine Cognitive



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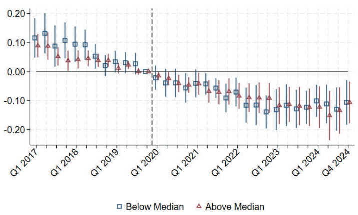

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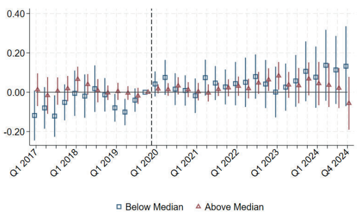

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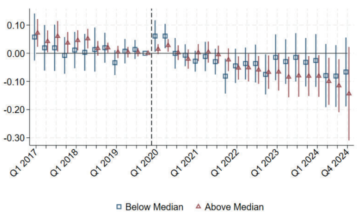

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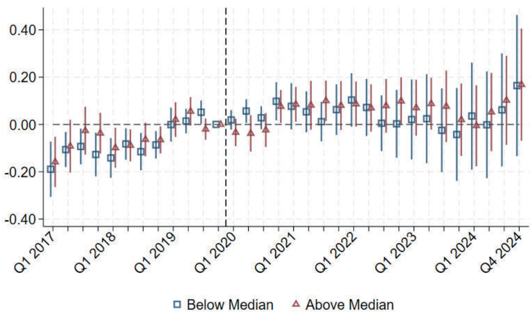
Figure 7: Event-Study Estimates of Skill Demand on Occupational WFH Feasibility (By Communication Technology Infrastructure)

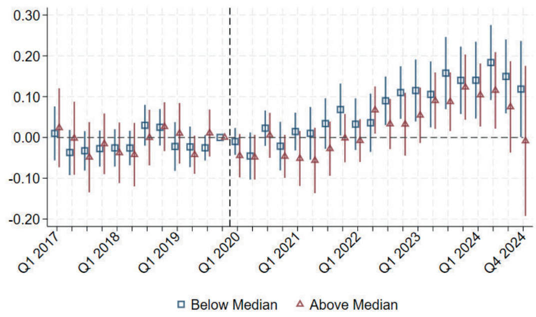
NOTE. — The estimated coefficients are based on a modified version of baseline eq. 5,interacted with a binary variable equal to one for a firm operating in an industry with above-medium communication technology infrastructure. Point estimates displayed with 95% confidence interval and N = 10,438,623. All regressions include regional controls, job-specific controls on formal requirements, firm FE, (2-digit) occupation FE, state FE, and source platform FE. Robust standard errors are clustered at the 3-digit+ occupation level as defined in section 4. Source: Palturai GmbH/Finbot AG (OJV data), BERUFENET (Skill terms), own calculations.

Industry Heterogeneity. Industries differed in their exposure to the pandemic depending on lockdown restrictions and remote-work feasibility (Schymik & Fadinger 2020). Essential sectors such as food retail or health care continued operations on-site, whereas many non-essential industries faced temporary shutdowns or had to reorganize work practices. In our framework, these differences determined how strongly in-person tasks were penalized and how far remote-feasible tasks could expand. To capture this heterogeneity, we re-estimate equation (5) separately for four broad industry groups: (i) Manufacturing, (ii) Retail and Logistics, (iii) Business Services, and (iv) Public, Social, and Personal Services.

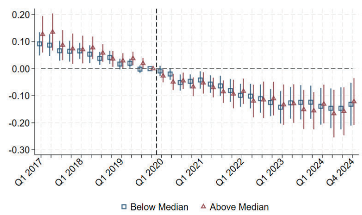
The results in Figure 9 highlight two main insights. First, the persistent rise in interactive skill demand is concentrated in Business Services, consistent with increasing importance of



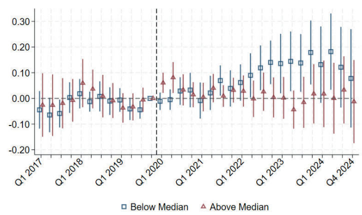
(a) Non-Routine Cognitive



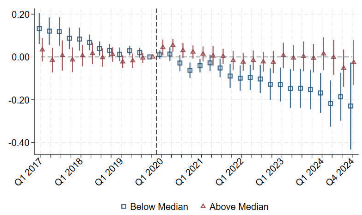
(b) Non-Routine Interactive



(c) Non-Routine Manual



(d) Routine Cognitive



(e) Routine Manual

Figure 8: Event-Study Estimates of Skill Demand on Occupational WFH Feasibility (Comparison of small versus large firms)

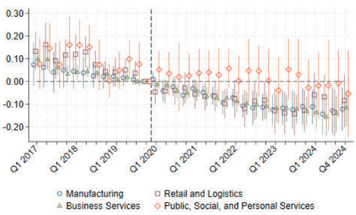
NOTE. — The estimated coefficients are based on a modified version of baseline eq. 5, interacted with a binary variable equal to one for a large firm (defined as above-medium employment size). Point estimates displayed with 95% confidence interval and N = 10,438,623. All regressions include regional controls, job-specific controls on formal requirements, firm FE, (2-digit) occupation FE, state FE, and source platform FE. Robust standard errors are clustered at the 3-digit+ occupation level as defined in section 4. Source: Palturai GmbH/Finbot AG (OJV data), BERUFENET (Skill terms), own calculations.

virtual collaboration and client interaction in office-based occupations, and to a smaller degree in Public and Social Services. Second, temporary increases in cognitive skill demand, both routine and NR, are driven primarily by firms in the manufacturing sector. Demand for NR cognitive skills also rose in Retail and Logistics, though less strongly. These temporary dynamics in the manufacturing sector came largely at the expense of manual skill demand.

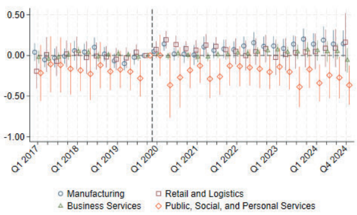
Taken together, Business Services drove the sustained rise in interactive skills, whereas manufacturing exhibited a shift away from manual toward cognitive skill requirements. These results reinforce our broader interpretation of the pandemic as a catalyst for organizational change rather than broad technological upgrading.

(a) Non-Routine Cognitive

(b) Non-Routine Interactive



(c) Non-Routine Manual



(d) Routine Cognitive

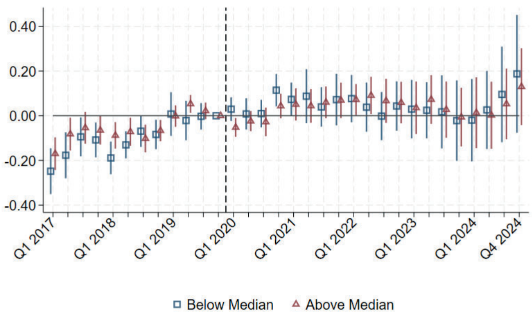
(e) Routine Manual

Figure 9: Event-Study Estimates of Occupational WFH Feasibility on Skill Demand (By industry groups)

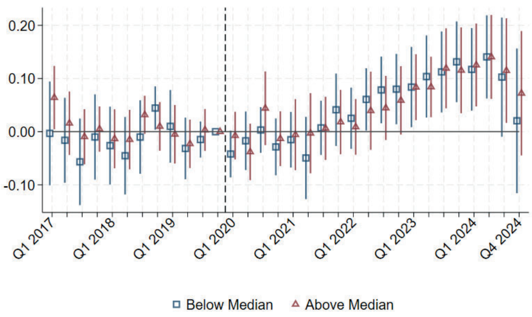
NOTE. — The estimated coefficients are based on a modified version of baseline eq. 5,interacted with a categorical variable capturing four different sectors (manufacturing, retail and logistics, business services, as well as public, social, and personal services. Point estimates displayed with 95% confidence interval and N = 10,438,623. All regressions include regional controls, job-specific controls on formal requirements, firm FE, (2-digit) occupation FE, state FE, and source platform FE. Robust standard errors are clustered at the 3-digit+ occupation level as defined in section 4. Source: Palturai GmbH/Finbot AG (OJV data), BERUFENET (Skill terms), own calculations.

Regional Heterogeneity: Unemployment. So far, our analysis has emphasized compositional and structural drivers of upskilling. Another prominent mechanism discussed in the literature is *cyclical upskilling*, which posits that firms become more selective and raise hiring requirements when they face a larger applicant pool (Modestino, Shoag & Ballance 2019). This channel implies stronger upskilling in regions with higher unemployment rates.

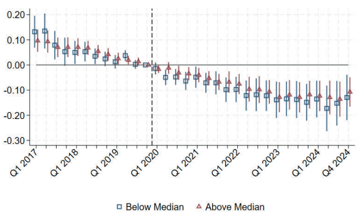
When applying this logic to Germany, however, Figure 9 suggests no differential skill demand responses across regions with varying unemployment levels. We interpret this null result as informative rather than puzzling. Unlike the US, Germany relied heavily on short-time work during the pandemic, similar to the Great Recession 2007/08 (Brinkmann, Jäger, Kuhn, Saidi & Wolter 2024; Kagerl 2024). This institutional feature dampened worker



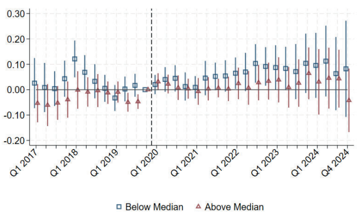
(a) Non-Routine Analytic



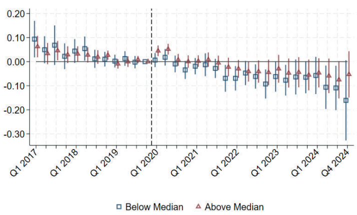
(b) Non-Routine Interactive



(c) Non-Routine Manual



(d) Routine Cognitive



(e) Routine Manual

Figure 10: Event-Study Estimates of Skill Demand on Occupational WFH Feasibility (By Regional Unemployment)

NOTE. — The estimated coefficients are based on a modified version of baseline eq. 5,interacted with a binary variable equal to one for a firm operating in a commuting zone with above-medium unemployment rates. Point estimates displayed with 95% confidence interval and N = 10,438,623. All regressions include regional controls, job-specific controls on formal requirements, firm FE, (2-digit) occupation FE, state FE, and source platform FE. Robust standard errors are clustered at the 3-digit+ occupation level as defined in section 4. Source: Palturai GmbH/Finbot AG (OJV data), BERUFENET (Skill terms), own calculations.

reallocation (Meriküll & Paulus 2024) and kept unemployment relatively low at around 6% (versus up to 15% in the US), thereby constraining the scope for cyclical upskilling. As a result, regional variation in unemployment was muted, likely reducing the economic relevance of the cyclical channel.

Overall, these findings underscore that in the German – and possibly broader European – context, post-pandemic shifts in skill demand were shaped primarily by structural rather than cyclical forces, consistent with a lasting reorganization of work within firms.

7 Conclusions

We study how economic crises reshape firms' skill demands, using the COVID-19 pandemic as a natural experiment in work reorganization. Drawing on 11 million German online job vacancies from 2017 to 2024, we use an event-study framework with continuous treatment intensity, where we exploit pre-pandemic variation in the feasibility of remote work across occupations within firms. Our research design compares how firms adjusted skill demand of otherwise similar jobs that differ in their potential to be performed remotely. This approach allows us to distinguish between short-term responses to pandemic constraints and more persistent shifts in skill demand.

COVID-induced changes in skill demand were largely short-lived, typically fading after one to three years. Yet one adjustment persisted: a sustained rise in interactive skill requirements in occupations with higher remote feasibility. When allowing for compositional adjustments across occupations, this persistence extends to cognitive skills as well, indicating even more pronounced upskilling at the extensive margin. These patterns point to a reorganization of work around hybrid collaboration, an organizational adjustment distinct from the crisis-driven acceleration of automation emphasized in the existing literature. Rather than automating or substituting routine tasks, lockdowns entailed task-specific constraints on physical presence that induced firms to reorganize collaboration at work.

We also show that persistent shifts in skill demand were driven by structural rather than cyclical forces. Lasting increases in interactive skill demand are concentrated in industries with advanced communication technology infrastructure, which enabled virtual collaboration to become a durable feature of work organization. In contrast, cyclical channels such as regional differences in unemployment played no meaningful role. Possibly, Germany's reliance on short-time work —mirroring similar job retention schemes across many European countries —helped stabilize employment and thus limited the scope for more selective hiring. These patterns indicate that post-pandemic skill adjustments reflect structural adaptation to hybrid work practices rather than cyclical fluctuations due to labor-market slack.

While our data capture a detailed and high-frequency view of employers' stated job requirements, it cannot fully represent the underlying task allocation or unobserved firm characteristics. Nonetheless, the results provide a consistent picture of how firms reorganized production in the post-pandemic era. For policymakers, our findings underscore that crises reshape not only employment levels but also the composition of skill demand. For firms, the results highlight that digital and communication technologies have created lasting complementarities with interactive capabilities, creating a key source of resilience in an increasingly hybrid world of work.

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Appendix

A Figures

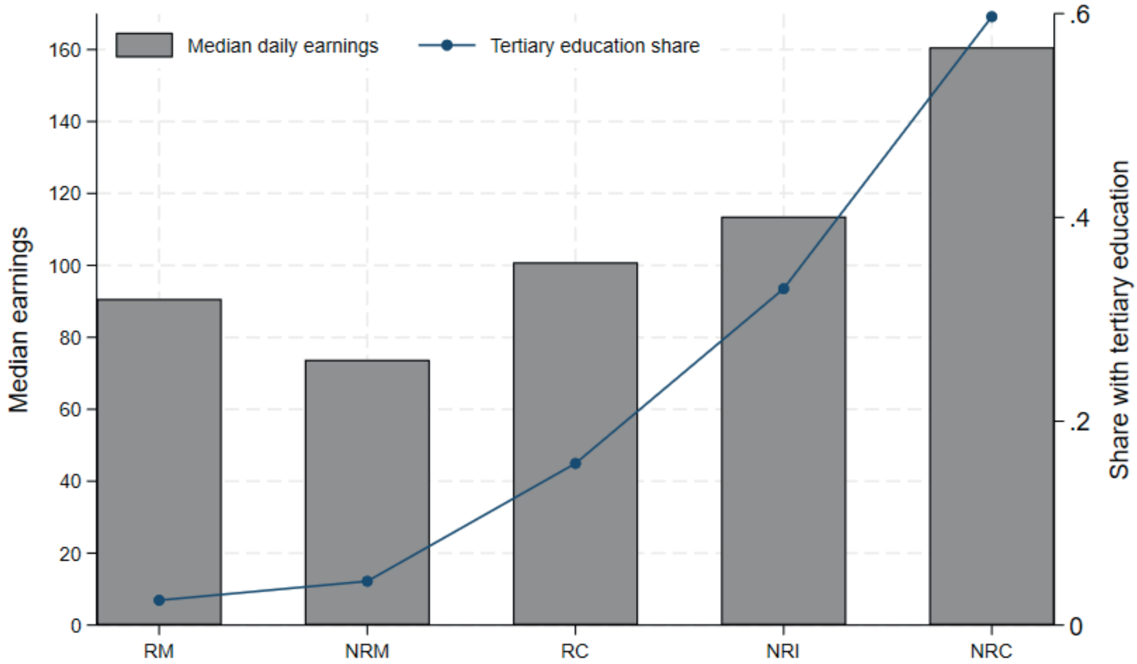
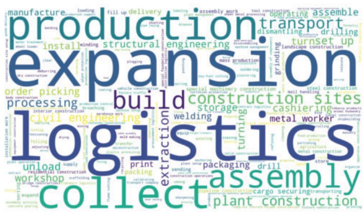


Figure A1: Earnings and Education Gradient Across Occupational Skill Groups

NOTE. — The figure shows median daily earnings (bars, left axis) and the share of workers with tertiary education (line, right axis) across five occupational skill groups. Source: IAB Occupation Panel (Grienberger, Janser & Lehmer 2023), own calculations.

Non-Routine Cognitive

Non-Routine Interactive



Non-Routine Manual

Routine Cognitive

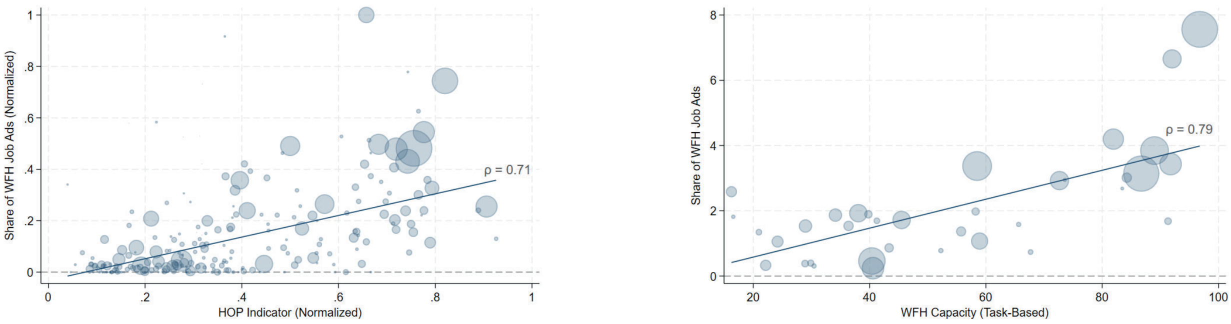
Routine Manual

Source: Own calculations based on Palturai GmbH/Finbot AG (OJV data), BERUFENET (skill terms), 2017–2024.

Figure A2: Word clouds of keywords within skill groups

Figure A3: Word Cloud of Terms Used to Identify Work-from-Home (WFH) Mentions in Job Postings

Source: Own calculations based on Palturai GmbH/Finbot AG (OJV data) 2017–2024.



(a) HOP-Indicator Bruns *et al.* (2025) (b) WFH Capacity Alipour *et al.* (2023)

Figure A4: External Validity of Work-From-Home Measure: Correlation with Alternative Measures

NOTE. — Panel A4a compares our vacancy-based WFH measure with the Home Office Potential (HOP) index developed by Bruns, Matthes & Stops (2025). The HOP index is based on occupational working conditions stated in the online job platform BERUFENET and reflects the potential WFH feasibility. Panel A4b compares our measure against the WFH Capacity Index from Alipour, Falck & Schüller (2023), which captures the WFH-feasibility based on worker-level survey data (BIBB/BAuA Employment Survey). The comparison with HOP index is at the 2-digit occupation-level and with the Alipour et al. measure at 2-digit level. Source: Own calculations based on Palturai GmbH/Finbot AG (OJV data), Bruns, Matthes & Stops (2025), and Alipour, Falck & Schüller (2023).

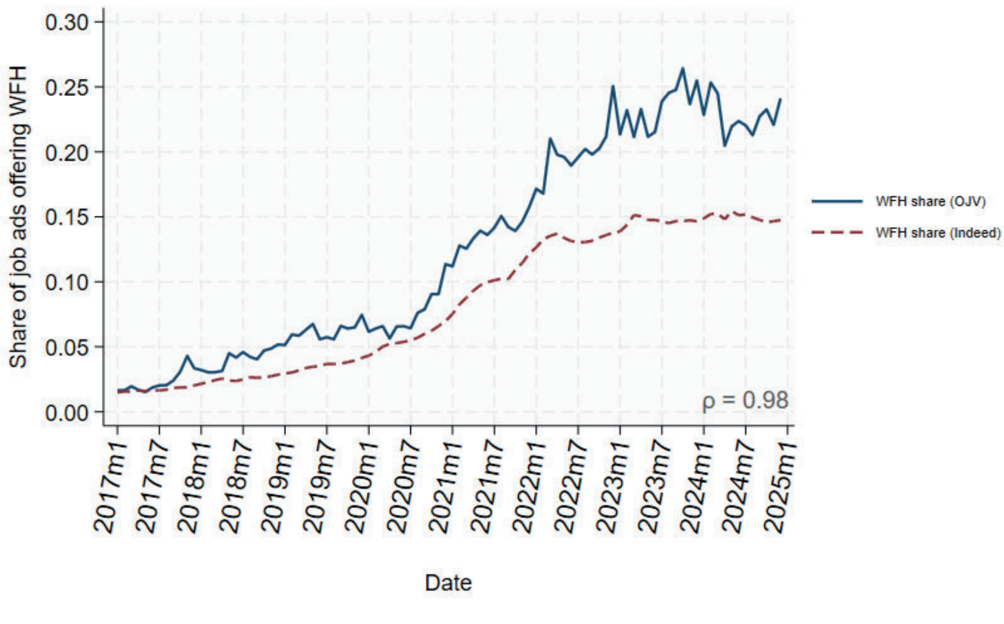


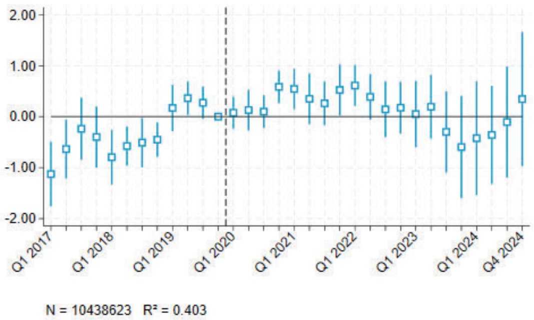
Figure A5: External Validity on Trends in WFH Options in Online Job Vacancies with Indeed data

NOTE. — This figure compares the share of job postings that mention WFH across two data sources: our OJV data provided by Paltura/ Finbot and publicly available data from the Indeed Hiring Lab. Source: Own calculations based on Palturai GmbH/Finbot AG and Indeed Hiring Lab.

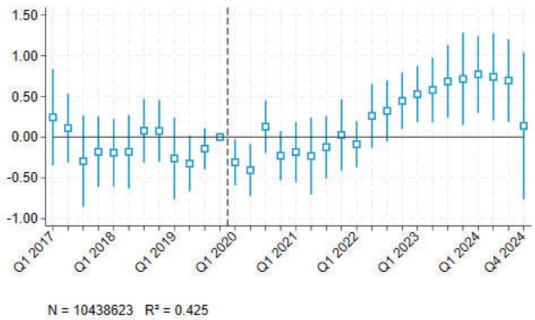
B Robustness Tests

B.1 Robustness Results

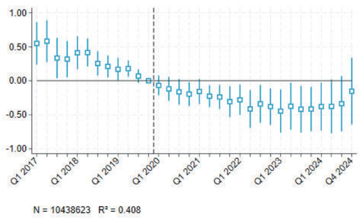
B.1.1 Selection Bias



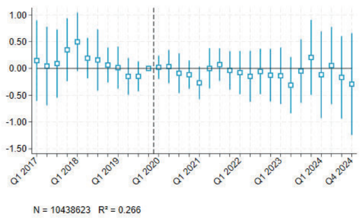
(a) Non-Routine Cognitive



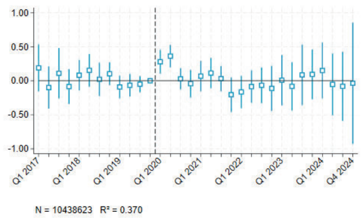
(b) Non-Routine Interactive



(c) Non-Routine Manual



(d) Routine Cognitive



(e) Routine Manual

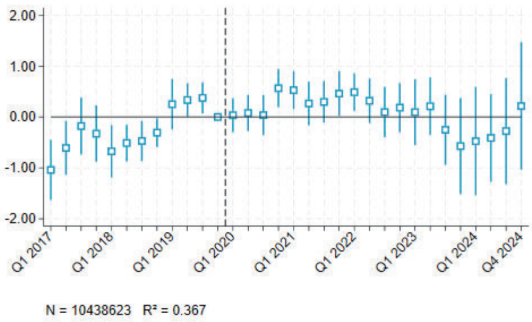
Figure A6: Robustness Check: Event-Study Estimates of Skill Demand on Occupational WFH Feasibility (Binary Treatment Specification, Unweighted)

NOTE. — The estimated coefficients are based on a modified version of baseline eq. 5, which uses a binary treatment, rather than continuous treatment, using the median as cutoff. Point estimates displayed with 95% confidence interval and N = 10,438,623. All regressions include regional controls, job-specific controls on formal requirements, 2-digit occupation FE (KLDB 2010), firm FE, state FE, and source platform FE. Robust standard errors are clustered at the 3-digit+ occupation level as defined in section 4. Source: Palturai GmbH/Finbot AG (OJV data), BERUFENET (Skill terms), own calculations.

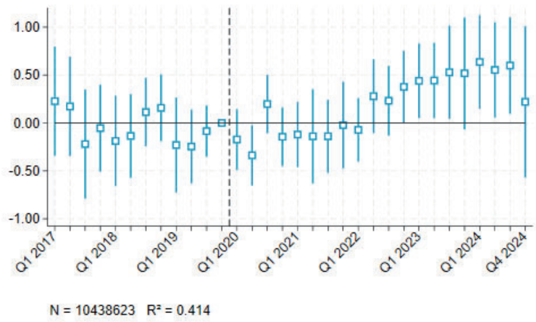
Table A1: Balancing Table

	Treat			**Control**		
Variable	Mean	Variance	Skewness	Mean	Variance	Skewness
	Unweighted Sample					
Firm Revenue	233,030	1.12×10^{11}	1.232	220,007	1.06×10^{11}	1.340
Firm Revenue NA	0.245	0.185	1.188	0.252	0.189	1.141
Firm Employment	4,304	1.04×10^{8}	2.992	4,912	1.16×10^{8}	2.653
Firm Employment NA	0.040	0.038	4.694	0.032	0.031	5.348
Urban Location	0.245	0.185	1.184	0.273	0.199	1.017
Rural Location	0.094	0.085	2.781	0.147	0.125	1.996
Rurality	10.340	410.700	2.149	15.640	575.700	1.512
Industry IT Infrastructure	708.100	373,887	2.772	624.800	598,947	2.722
	Weighted Sample					
Firm Revenue	233,030	1.12×10^{11}	1.232	233,030	1.12×10^{11}	1.232
Firm Revenue NA	0.245	0.185	1.188	0.245	0.185	1.188
Firm Employment	4,304	1.04×10^{8}	2.992	4,304	1.04×10^{8}	2.992
Firm Employment NA	0.040	0.038	4.694	0.040	0.038	4.694
Urban Location	0.245	0.185	1.184	0.245	0.185	1.184
Rural Location	0.094	0.085	2.781	0.094	0.085	2.781
Rurality	10.340	410.700	2.149	10.340	410.700	2.149
Industry IT Infrastructure	708.100	373,887	2.772	708.100	373,893	2.772

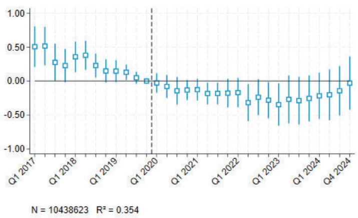
Note: The control group consists of 6,737,611 observations and the treatment group of 4,494,842 observations.



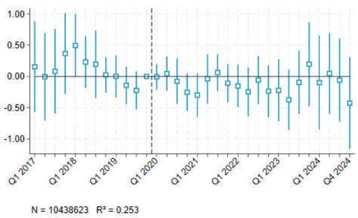
(a) Non-Routine Cognitive



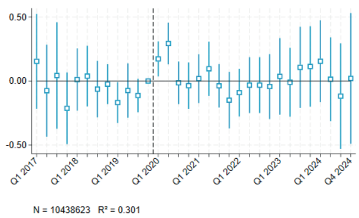
(b) Non-Routine Interactive



(c) Non-Routine Manual



(d) Routine Cognitive

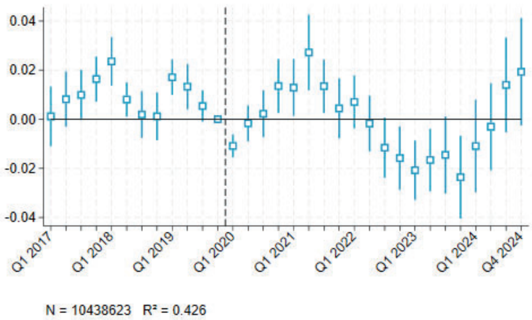


(e) Routine Manual

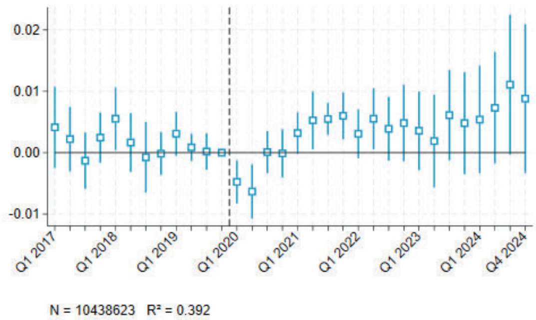
Figure A7: Robustness Check: Event-Study Estimates of Skill Demand on Occupational WFH Feasibility (Binary Treatment and Weighted Sample using Entropy Balancing)

NOTE. — The estimated coefficients are based on a modified version of baseline eq. 5, which uses a weighted binary treatment, rather than continuous treatment, using the median as cutoff. Treatment and control group are matched based on entropy balancing (see Table A1 for a balancing table). Point estimates displayed with 95% confidence interval and N = 10,438,623. All regressions include regional controls, job-specific controls on formal requirements, 2-digit occupation FE (KLDB 2010), firm FE, state FE, and source platform FE. Robust standard errors are clustered at the 3-digit+ occupation level as defined in section 4. Source: Palturai GmbH/Finbot AG (OJV data), BERUFENET (Skill terms), own calculations.

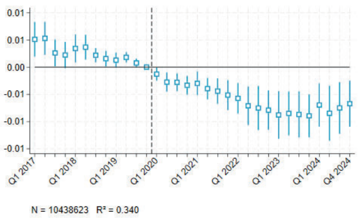
B.1.2 Outcome Definitions



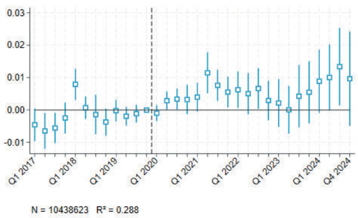
(a) Non-Routine Cognitive



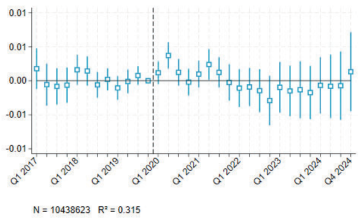
(b) Non-Routine Interactive



(c) Non-Routine Manual



(d) Routine Cognitive



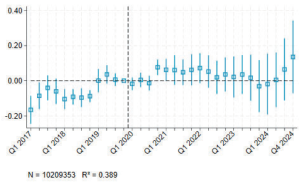
(e) Routine Manual

Figure A8: Mechanism Analysis: Event-Study Estimates of Skill Demand on Occupational WFH Feasibility (Skill Counts per Job Ad)

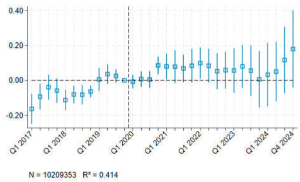
NOTE. — The estimated coefficients are based on a modified version of baseline eq. 5, using an *absolute* skill measure (number of skills per job ad) instead of the baseline *relative* measure capturing the share of each skill group. Point estimates displayed with 95% confidence interval and N = 10,438,623. All regressions include regional controls, job-specific controls on formal requirements, firm FE, (2-digit) occupation FE, state FE, and source platform FE. Robust standard errors are clustered at the 3-digit+ occupation level as defined in section 4. Source: Palturai GmbH/Finbot AG (OJV data), BERUFENET (Skill terms), own calculations.

Table A2: Skill Clusters Used in Leave-One-Out Analyses

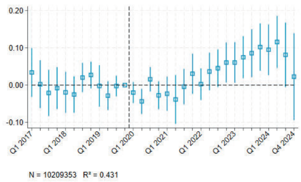
Skill Group	**Skill Cluster Name**	**Included Skills (Keywords)**
NRC	Project & Product Management	project management, software development, project leadership, construction, product management, project planning, prototyping, project execution, process management, editing, production planning, software architecture, project development, system architecture, project coordination, energy management, system development, hardware development, license management, software design, marketing concept, production management, software engineering, innovation management, project responsibility, product design, process control, software implementation, agile project management, energy distribution, project team leadership, cultural management, hotel management
NRC	Leadership & Strategic Tasks	lead, develop, take responsibility, manage, prepare, estimate, determine, medical, assess, explore, science, investigate, finance
NRI	Team Collaboration	collaboration with
NRI	Client Support & Consulting	customer consulting, customer support, advise customers, customer assistance, customer care, customer service, acquire customers, customer acquisition, serve customers, customer training, customer reception, customer recovery
NRI	Sales & Transactions	sales, purchasing, sell, briefing, present, entertain, shop, welcome, instruct, technical purchasing, rent out
NRI	Retail & Client Relations	retail, field sales, contract negotiations, HR, public relations, supplier management, foreign trade, social work, tax consulting, aftercare, wholesale, business management, import, teamwork, renting, direct sales, technical sales, specialty store, purchasing and procurement, specialist advice, event management, real estate financing, youth work, telephone service, press work, home visits, waste management, information services, advertising agency, food trade, passenger transport, sales department, social management, applicant selection, discharge management, individual care, member support, corporate clients, funding programs, mail order, energy trade, energy consulting, debt counseling, health consulting, giving lectures, retail banking, lecture activity, store, book trade, day-care facilities, access control, shift management, ward service, career counseling, household goods, timber trade
RC	German Language Proficiency	German



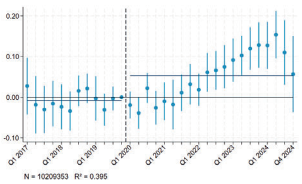
(a) NR Cognitive: No Project, Product, and Process Management



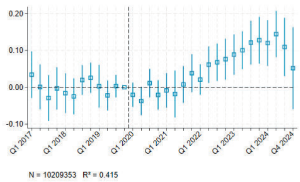
(b) NR Cognitive: Leadership, Strategy, and Evaluation



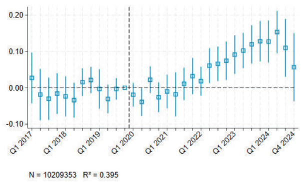
(c) NR Interactive: No Collaboration



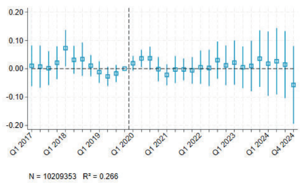
(d) NR Interactive: No Retail, Trade, and Client Relations



(e) NR Interactive: No Customer Service and Consulting



(f) NR Interactive: No Sales and Client Transactions

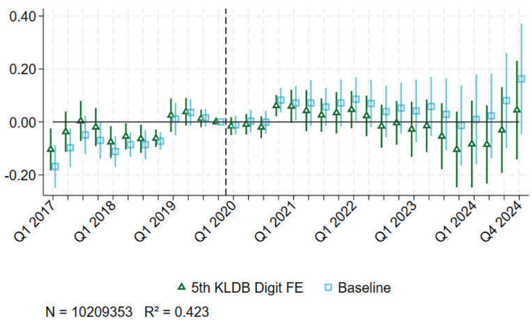


(g) Routine Cognitive: No German language proficiency

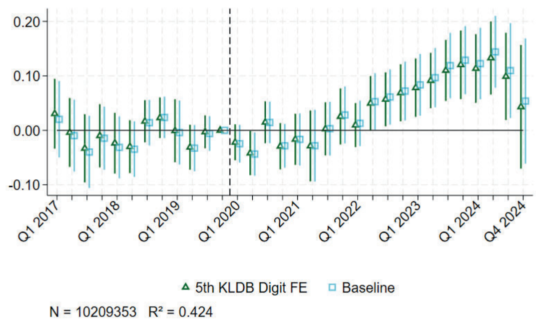
Figure A9: Robustness: Event-Study Estimates of Skill Demand on Occupational WFH Feasibility (Leave-One-Out analysis, by Skill Cluster)

NOTE. — The estimated coefficients are based on a modified version of baseline eq. 5, which omits certain skill clusters from the main analysis. Point estimates displayed with 95% confidence interval and N = 10,209,353. All regressions include regional controls, job-specific controls on formal requirements, firm FE, (2-digit) occupation FE, state FE, and source platform FE. Robust standard errors are clustered at the 3-digit+ occupation level as defined in section 4. Source: Palturai GmbH/Finbot AG (OJV data), BERUFENET (Skill terms), own calculations.

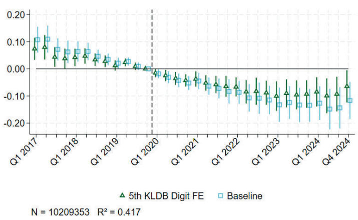
B.1.3 Model Specification



(a) Non-Routine Cognitive



(b) Non-Routine Interactive



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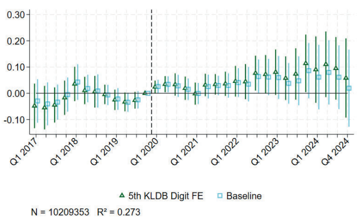
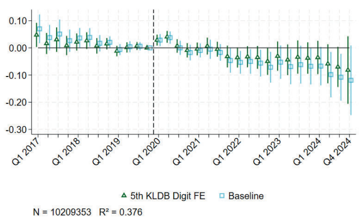


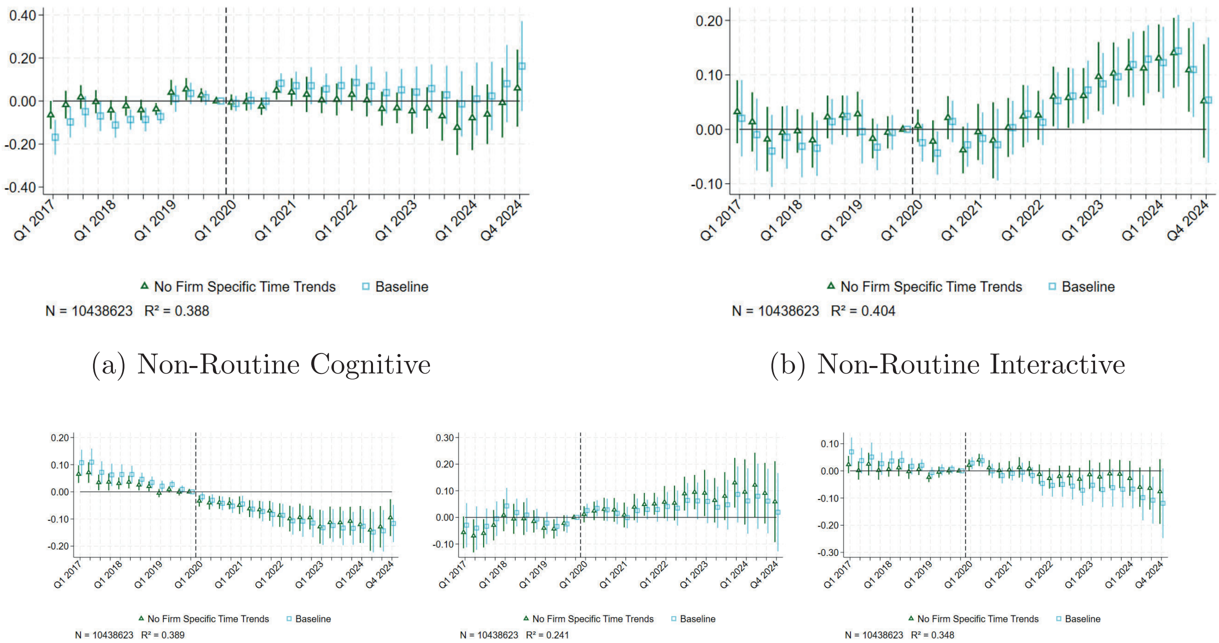
(d) Routine Cognitive



(e) Routine Manual

Figure A10: Robustness Check: Event-Study Estimates of Skill Demand on Occupational WFH Feasibility (Occupation Fixed Effects defined at fifth level)

NOTE. — The estimated coefficients are based on a modified version of baseline eq. 5, including occupation fixed effects at the fifth digit rather than the second digit as in the main analysis. The fifth digit captures variation in job complexity within broader occupational groups. Point estimates displayed with 95% confidence interval and N = 10,209,353. All regressions include regional controls, job-specific controls on formal requirements, firm FE, state FE, and source platform FE. Robust standard errors are clustered at the 3-digit+ occupation level as defined in section 4. Source: Palturai GmbH/Finbot AG (OJV data), BERUFENET (Skill terms), own calculations.



(a) Non-Routine Cognitive

(b) Non-Routine Interactive

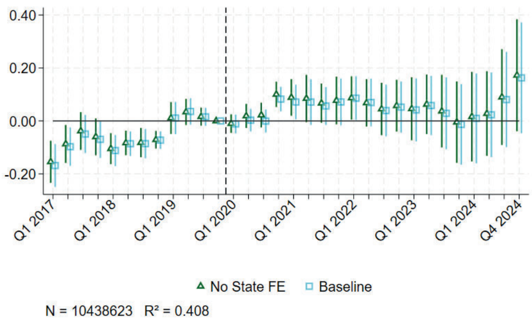
(c) Non-Routine Manual

(d) Routine Cognitive

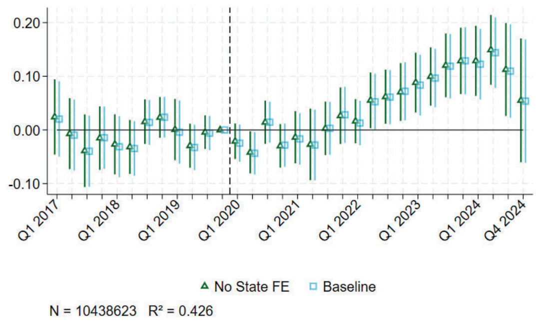
(e) Routine Manual

Figure A11: Robustness Check: Event-Study Estimates of Skill Demand on Occupational WFH Feasibility (Standard Firm Fixed Effects)

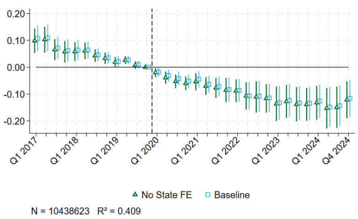
NOTE. — The estimated coefficients are based on a modified version of baseline eq. 5, which uses standard firm fixed effects instead of firm-specific linear trends. Point estimates displayed with 95% confidence interval and N = 10,438,623. All regressions include regional controls, job-specific controls on formal requirements, (2-digit) occupation FE, state FE, and source platform FE. Robust standard errors are clustered at the 3-digit+ occupation level as defined in section 4. Source: Palturai GmbH/Finbot AG (OJV data), BERUFENET (Skill terms), own calculations.



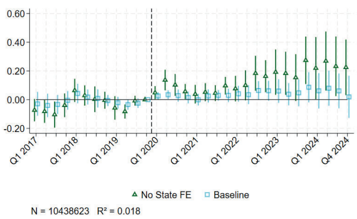
(a) Non-Routine Cognitive



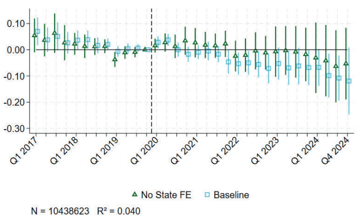
(b) Non-Routine Interactive



(c) Non-Routine Manual



(d) Routine Cognitive

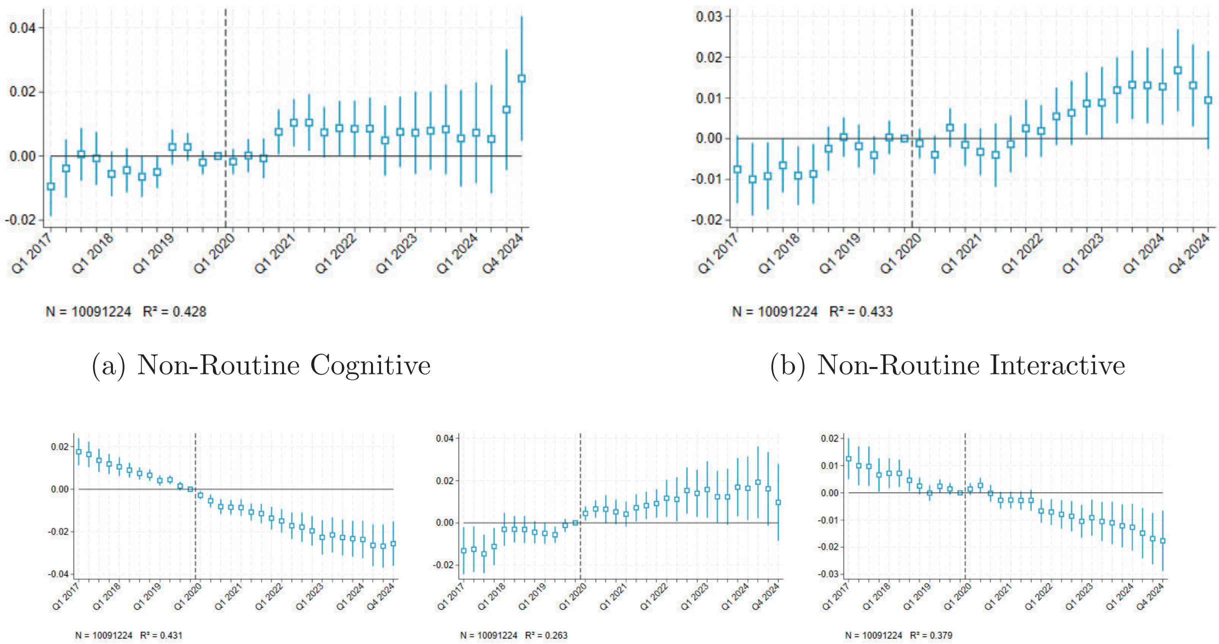


(e) Routine Manual

Figure A12: Robustness Check: Event-Study Estimates of Skill Demand on Occupational WFH Feasibility (Excluding State Fixed Effects)

NOTE. — The estimated coefficients are based on a modified version of baseline eq. 5, which omits state fixed effects and thus exploits variation within occupations but across states. Point estimates displayed with 95% confidence interval and N = 10,438,623. All regressions include regional controls, job-specific controls on formal requirements, firm FE, (2-digit) occupation FE, and source platform FE. Robust standard errors are clustered at the 3-digit+ occupation level as defined in section 4. Source: Palturai GmbH/Finbot AG (OJV data), BERUFENET (Skill terms), own calculations.

B.1.4 External Validity of WFH Measure



(a) Non-Routine Cognitive (b) Non-Routine Interactive

(c) Non-Routine Manual (d) Routine Cognitive (e) Routine Manual

Figure A13: Robustness Check: Event-Study Event-Study Estimates of Skill Demand on Occupational WFH Feasibility (Using External Home Office Measure)

NOTE. — The estimated coefficients are based on a modified version of baseline eq. 5, which uses an external measure of Home Office Potential (HOP) developed by Bruns, Matthes & Stops (2025). The HOP index is based on occupational working conditions stated in the online job platform BERUFENET and reflects the potential WFH feasibility. Point estimates displayed with 95% confidence interval and N = 10,091,224. All regressions include regional controls, job-specific controls on formal requirements, firm FE, (2-digit) occupation FE, state FE, and source platform FE. Robust standard errors are clustered at the 3-digit+ occupation level as defined in section 4. Source: Palturai GmbH/Finbot AG (OJV data), BERUFENET (Skill terms), Bruns, Matthes & Stops (2025) (HOP measure), own calculations.

C Details on Task-Based Framework and Remote Work Extension

This appendix derives the comparative statics underlying our theoretical framework. We start from the canonical task-based model (Acemoglu & Autor 2011), where each task i can be performed by low-, medium-, or high-skill workers with task-specific productivities $\alpha_j(i)$ and factor-augmenting technologies A_j.[1] The production function for a given task is

$$y(i) = A_L \alpha_L(i) l(i) + A_M \alpha_M(i) m(i) + A_H \alpha_H(i) h(i). \tag{1}$$

Because comparative advantage schedules differ across groups, the task space is partitioned into three domains with cutoffs I_L and I_H. In equilibrium, these thresholds are determined by no-arbitrage conditions that equalize the effective costs of performing tasks at the boundaries:

$$A_L \alpha_L(I_L) \frac{L}{I_L} = A_M \alpha_M(I_L) \frac{M}{I_H - I_L}, \tag{2a}$$

$$A_M \alpha_M(I_H) \frac{M}{I_H - I_L} = A_H \alpha_H(I_H) \frac{H}{1 - I_H}. \tag{2b}$$

To capture the impact of COVID-related restrictions, we extend the model by introducing group- and task-specific penalties for remote-incompatible work. Let $\psi_j(i) \in [0, 1]$ denote the degree of remote feasibility of task i for skill group j. Effective productivity thus becomes

$$\tilde{A}_j(i) = A_j \alpha_j(i) \psi_j(i). \tag{3}$$

where $\psi_j(i)$ scales down productivity whenever tasks are not fully remote-feasible. Lower $\psi_j(i)$ values imply stronger penalties for tasks tied to on-site presence, while higher $\psi_j(i)$ imply low penalties. Substituting (3) into the no-arbitrage conditions (2a) and (2b) yields

[1] Unlike the canonical model, we omit potential substitution of labor by capital to keep the exposition centered around the relevant margins of adjustment for our purposes.

$$A_L \alpha_L(I_L)\psi_L(I_L)\,\frac{L}{I_L} = A_M \alpha_M(I_L)\psi_M(I_L)\,\frac{M}{I_H - I_L}, \tag{4a}$$

$$A_M \alpha_M(I_H)\psi_M(I_H)\,\frac{M}{I_H - I_L} = A_H \alpha_H(I_H)\psi_H(I_H)\,\frac{H}{1 - I_H}. \tag{4b}$$

Consider the lower boundary (4a). Taking logs and totally differentiating while holding technology A_j, labor suply $(L,\ M)$, and baseline productivity α_j fixed, we can rearrange terms and multiply through by $I_L(I_H - I_L)$ to isolate ΔI_L:

$$\Delta I_L = \frac{I_L(I_H - I_L)}{I_H}\, r_L \;+\; \frac{I_L}{I_H}\,\Delta I_H. \tag{5}$$

where $r_L \equiv \Delta \ln\left(\frac{\psi_L}{\psi_M}\right)\Big|_{I_L}$. Equation (5) shows that the movement of the lower cutoff depends directly on the relative penalty shock of lesser- and medium-skilled workers at the boundary (r_L) and on the adjustment of the upper cutoff. The term $\frac{I_L(I_H - I_L)}{I_H}$ is strictly positive, so ΔI_L always moves in the same direction as r_L. Analogously, starting from the upper boundary condition (4b) and rearranging yields

$$\Delta I_H = \frac{(1 - I_H)(I_H - I_L)}{1 - I_L}\, r_H \;+\; \frac{1 - I_H}{1 - I_L}\,\Delta I_L. \tag{6}$$

Substituting (6) into (5) and vice versa, we can derive closed-form solutions for both cutoffs:

$$\Delta I_L = I_L(1 - I_L)\, r_L \;+\; I_L(1 - I_H)\, r_H, \tag{7a}$$

$$\Delta I_H = (1 - I_H) I_H\, r_H \;+\; (1 - I_H) I_L\, r_L. \tag{7b}$$

Both expressions consist of a first-order effect from the boundary-specific penalty shock (first time) and a spillover from the other boundary's shock (second term). Taking the derivative with respect to the penalty shocks in (7a) and (7b) then implies:

$$\frac{\partial \Delta I_L}{\partial r_L} = I_L(1 - I_L) > 0, \quad \frac{\partial \Delta I_L}{\partial r_H} = I_L(1 - I_H) > 0,$$

$$\frac{\partial \Delta I_H}{\partial r_H} = (1 - I_H)I_H > 0, \quad \frac{\partial \Delta I_H}{\partial r_L} = (1 - I_H)I_L > 0.$$

Because all coefficients are strictly positive and $0 < I_L < I_H < 1$, each boundary responds most strongly to its own penalty shock while also being influenced—albeit to a lesser extent—by the other boundary's shock through the cross-weights $I_L(1 - I_H)$ and $(1 - I_H)I_L$.

Under the key assumption $\psi_L < \psi_M < \psi_H$ —that is, lower-skilled workers experience larger remote-work penalties —we obtain $r_L < 0$ and $r_H < 0$, implying $\Delta I_L < 0$ and $\Delta I_H < 0$. The low-skill domain therefore contracts, the high-skill domain expands, and the net effect on the medium-skill domain depends on the relative magnitudes of both shifts.

Online Appendix: Data Preparation

OA.1 NLP Steps for preparation of Vacancy Data

Upon receiving the data from Finbot, we link firm and vacancy information and perform the necessary steps to preprocess the textual data, following the conventions of the literature (Ash & Hansen 2023; Gentzkow, Kelly & Taddy 2019). Beyond these basic steps, we enrich the data as follows. First, we assign each vacancy to a specific location, either at the zip code (39% of OJVs), municipality-level (48%), or county-level (10%).[2] Overall, we can thus assign 97% of job postings to a specific county.[3] Second, we classify job titles according to the German Classification of Occupations 2010 (KldB 2010). For this purpose, we use official, codified job titles at the 5-digit level, which are provided by the Federal Employment Agency (BA). Extracting job titles from our vacancies, and comparing their job description with the BA, we can immediately assign job titles to 3-digit occupations for about 60% of vacancies. In a follow-up step, we classify the remaining job titles by annotating a sample of not-yet-classified vacancies.

A key step in the preparation of OJV data is the identification of distinct text segments —a process referred to as "Zoning".[4] A typical usually (or ideally) contains four distinct text segments: a description of (i) relevant job activities and (ii) qualifications, (iii) benefits offered by the company, and (iv) a company description. However, not all of these segments are always available in a given posting.

To extract the different segments from the job descriptions, we follow a two-step approach.

[2] About 10% of job postings lack specific working place location information (typically smaller companies operating in one specific region). In such cases, we use the address provided in the imprint as the basis for regional allocation

[3] If multiple work locations are specified and those locations span several counties, the job posting is proportionally allocated across the respective counties.

[4] For details on essential steps in the preparation of online job vacancies we refer the interested reader to the OJA Guide —a dashboard to provides useful information on collecting, processing, and analyzing online job vacancy data. This guide was initiated by the Bertelsmann Stiftung and the Federal Institute for Vocational Education and Training, and was in large part prepared by project manager and main author is Johannes Müller (&effect data solutions) —an expert with extensive experience in working with online job vacancy data.

First, we use a large language model—specifically ChatGPT-4-mini—to extract four sections from the full text of each raw vacancy, omitting text that is not relevant for the job description (e.g., HTML remnants, contact information, etc.). For this purpose, we manually label 50,000 job postings. Second, we use these labeled data to fine-tune a German-language BERT model. The BERT model is configured as a token classifier and predicts, for each token in a job description, whether it belongs to one of the defined sections or to the residual section. Out-of-sample, the model achieves F1 scores of 95.38% for job activities, 97.37% for qualifications, 97.22% for benefits, and 91.07% for company descriptions. After a manual validation step, we apply the trained model to perform the zoning procedure on all job vacancies.

Another important step in preparing the OJV data is the detection of duplicate job postings. While Palturai/Finbot removes duplicates within the same platform, the same vacancy may still appear on different websites. To identify such duplicates with manageable computational effort, we apply the following preconditions: jobs must have been posted (i) by the same firm, (ii) in the same location, (iii) for the same occupation, and (iv) within a 60-day window. We then compare the textual similarity of the extracted segments. Based on a manually labeled dataset of 1,500 potential duplicates, we find that the model calculating pairwise partial Levenshtein distances solely on the job activities segment, with a similarity threshold of 90%, achieves the best performance (F1 score: 91.02%). Applying this model, we conclude that 13% of job postings should be classified as duplicates and are therefore excluded from further analysis.

For the purpose of this study, we concentrate on information provided in the description of job activities and qualifications. To this end, we create a comprehensive keyword list, which we use to track firms' job requirements over time (see section OA.4 for more details). While a keyword-based approach is simple and straightforward, it is also susceptible to picking up false positives (e.g., misleading context of a job task). To alleviate such concerns, we adopt an n-gram approach, in which we combine multiple search terms. For example, the task "[to] support" can mean many things and bears a high risk of picking up false positives. In conjuncture with "clients", in turn, the task "support clients" reduces that risk. For our n-gram approach, we identify job-specific skill requirements, consisting of multiple search terms, if those terms are mentioned within a 5-word window in the job description.

OA.2 Sample Selection

For our analysis, we limit ourselves to vacancies advertising regular employment, i.e., full- or part-time positions. To this end, we remove vacancies seeking apprenticeships, internships, student or temporary assistant jobs, using a keyword-based approach.

We exclude vacancies without a valid firm identifier, as well as those for which no industry code is available. In addition, we remove vacancies from temporary employment agencies and large recruitment intermediaries. To improve the classification provided by Finbot/Palturai, we further exclude firms whose industry code starts with N78.1 (temporary employment activities) and 159 manually identified personnel placement agencies. Temporary work agencies typically seek employees with flexible work schedules and therefore post broader job descriptions and requirements.[5] We also drop postings for which no occupational classification (KldB 2010) could be extracted from the job title.

To ensure the reliability of our text segmentation procedure, we remove job advertisements exceeding 3,000 tokens, as these typically combine several distinct vacancies within a single posting. Moreover, we exclude vacancies where no task section could be identified in the zoning step, as well as all postings flagged as duplicates.

For our analysis, we limit ourselves to vacancies advertising regular work, i.e. full- or part-time. To this end, we remove vacancies seeking apprenticeships, trainees, and other types of irregular work. In particular, we drop vacancies for temporary employment and large recruitment agencies because temporary work agencies typically look for employees with more flexible work schedules and therefore advertise somewhat broader job descriptions

[5]See Stops, Bächmann, Glassner, Janser, Matthes, Metzger & Müller, Christoph, Seitz, Joachim (2021) for a detailed discussion on this issue.

and requirements.[6] For similar reasons, we restrict our dataset to job advertisements from companies that can be linked to the business register. We also exclude job postings with more than 3000 tokens. These postings mostly provide misleading information, thus adding unnecessary noise. We also exclude vacancies that are lacking a job profile section, a section on skills or qualification requirements, or any identifiable skills

In order to maintain a balanced sample, we impose two more restrictions. One, we exclude observations with missing data on either date, location or occupations. Two, we restrict our sample to firms that have posted vacancies between 2018 and 2022 (i.e. two years prior to and after the pandemic). While we lose about 15% of observations with these restrictions, this balanced sample allows us to focus on firms that regularly post job vacancies and abstract from firm entries and exits.

OA.3 External Validity & Representativeness of OJV Data

A common concern with vacancy data is representativeness. Table OA1 shows that posting firms in our sample are around 26 years old and employ 4,900 workers, with 87% located in urban areas. These patterns suggest that our data primarily reflect larger, well-established firms in metropolitan labor markets, consistent with where most professional hiring occurs. To bolster the external validity of our analysis, we provide two pieces of supporting evidence. First, we show below that aggregate vacancy trends in our data closely mirror those reported by the (representative) IAB Job Vacancy Survey (Bossler, Gürtzgen, Kubis, Küfner & Popp 2021). Second, we present re-weighting analyses in the paper to demonstrate the robustness of our baseline results across distinct weighing schemes (section 5.2).

Aggregate Trends in Labor Demand Figure OA1a compares the monthly inflow of online job ads from 2017 – 2024 in our vacancy data (Panel) with the stock of vacant positions taken from the IAB Job Vacancy Survey. Both display a steady increase in postings from

[6] See Stops, Bächmann, Glassner, Janser, Matthes, Metzger & Müller, Christoph, Seitz, Joachim (2021) for a detailed discussion on this issue.

Table OA1: Summary Statistics of Posting Firms and Vacancy Characteristics

	Mean	SD
Firm Age (in years)	25.77	17.87
Workforce Size	4,873.51	10,843.88
Region: Agglomeration	0.60	0.49
Region: Urban	0.27	0.44
Region: Rural	0.13	0.34
Share of Non-Routine Cognitive Skills	0.43	0.29
Share of Non-Routine Interactive Skills	0.19	0.23
Share of Non-Routine Manual Skills	0.08	0.17
Share of Routine Cognitive Skills	0.21	0.22
Share of Routine Manual Skills	0.09	0.17
Observations	11,232,453	

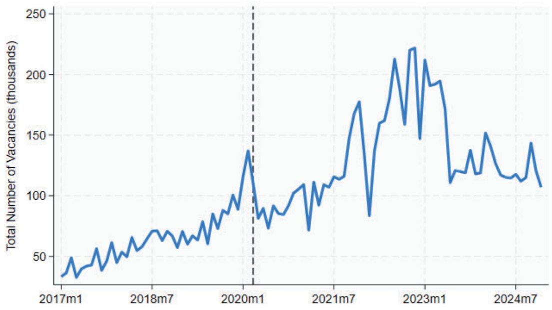
NOTE. —This table reports summary statistics for firms posting online job vacancies between 2017 and 2024. Means and standard deviations (SD) are reported for all variables. Source: BERUFENET (Skill terms), Palturai GmbH/Finbot AG (OJV data), own calculations.

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 in on the IAB Job Vacancy Survey, the inflows of vacancies in our OJV data decreased by 30% from December 2019 until June 2020.

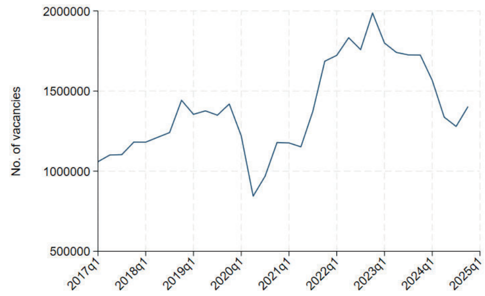
Both time series also illustrate a sharp subsequent rebound, leading to a catch-up to pre-COVID vacancy levels in the second half of 2021. Moreover, the magnitude of the drop and rebound in job vacancies during the pandemic is consistent with previous findings in the literature from comparable countries, 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 2020).

Starting in 2021, we observe a steady increase in the number of online job vacancies and the stock of open positions alike, which peaks at the end 2022 in both data sources. Since early 2023, labor demand has cooled off, which is clearly visible in both data sets. Compared to its peak in the end of 2024, the number of monthly job postings in our OJV data dropped by around 40%. In comparison, the number of open positions in the IAB Job Vacancy survey declined by about 30%.

Taken together, both our OJV data and the IAB Job Vacancy survey display very similar



(a) OJV data, by source (Inflow)



(b) IAB Job Vacancy Survey (Stock)

NOTE. —Panel OA1a 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 OA1b displays the stock of vacancies firms report to the IAB for each quarter from 2017 until 2024.

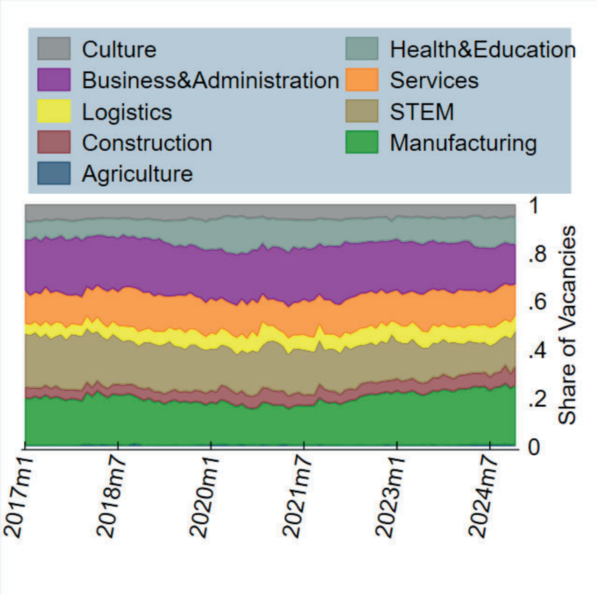
Figure OA1: Number of Vacancies over Time, 2017-01 - 2024-12

stylized facts from 2017 - 2024. The key difference lies in the higher levels of volatility in the OJV data, in part because this data represents flow variables rather than the stock variables contained in the survey data.

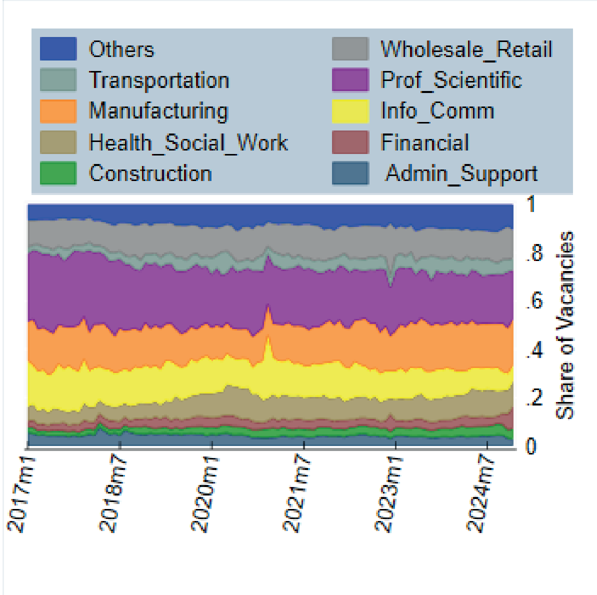
Trends in Labor Demand by Occupations and Industries. Beyond the aggregate consistency in vacancy trends outlined above, we also break down job postings by broad occupational (1-digit KldB 2010) and industry groups (approximately 1-digit WZ08). Figure OA2 provides insights into how the composition of posted vacancies evolved between 2017 and 2024.

Panel OA2a displays the distribution of job postings by broad occupational groups. Early in the observation period, postings were heavily concentrated in occupations related to Business & Administration and STEM roles, accounting for around 40% of all job postings combined. Over time, the composition has become more balanced, however. Especially occupations related to Manufacturing and Health & Education have become increasingly prominent in online job postings, reflecting increased online recruiting activity in these labor market segments.

Panel OA2b shows similar trends at the industry level. In 2017, postings were heavily concentrated in professional services, accounting for about 30% of all job postings. By 2024, these services merely accounted for around 20% of online job vacancies. Similar observations



(a) By occupational group (1-digit KldB2010)



(b) By industry group (≈ 1-digit WZ08)

Figure OA2: Composition of Online Job Vacancies by occupations and industries: 2017 - 2024

NOTE. — Panel OA2a displays the changing occupational composition of online job vacancies based on broad occupational groups, following the German classification of occupations 2010 (KldB 2010, 1-digit definition). Panel OA2b shows the corresponding trends by broad industry groups, following the German classification of industries WZ08. Our industries represent an aggregated version of NACE-2 sectors. Source: Palturai GmbH/Finbot AG (OJV data), own calculations.

can be found for the ICT industry. In contrast, postings in Manufacturing, Transportation, and Health-and social related industries have expanded considerably over time. These trends suggest that online job postings, which were once skewed toward high-skill, white-collar occupations, now more comprehensively reflect the broader economy, including blue-collar work. The changing sectoral and occupational composition in the OJV data also has implications for observed shifts in skill demand. As online vacancies become more evenly distributed across the labor market, the relative importance of non-STEM occupations —such as logistics, care work, or manual production —in online job postings increases.

Taken together, our analysis shows that white-collar and high-skilled jobs are still somewhat dominant in the composition of online job vacancies. Yet, a more balanced composition over time underscores the increasing representativeness of online job vacancies as a data source for labor market analysis and enhances the external validity of analyses based on OJV data.

OA.4 Details on Skill Classification

In this section we describe in detail the construction of our skill measures. To this end, we transform raw information from the job portal BERUFENET into a data structure that suitable for econometric analysis. BERUFENET, a database analogous to O*NET and ESCO, provides a rich source of job requirements, encompassing tasks, skills, certificates, and technologies.

In the first step, we collect approximately 8,700 job requirements directly from BERUFENET. These raw entries, however, are not immediately suitable for our purpose, as they blend distinct concepts such as skills, tasks, certificates, and technologies. In principle, we view skills, certificates, and tasks interchangeably in the context of analyzing job vacancies, though, conceptually different from technologies. While technologies represent tools or products workers use at work (e.g. the business intelligence technology Tableau), the remaining concepts —skills, tasks, and certificates —represent qualifications that suitable applicants need to possess in order to work with said tool (e.g. performing data visualization with Tableau). By prompting ChatGPT 4o with our distinction —tools/products represent technologies while skills, tasks, and certificates reflect qualification —we thus separate these two classes of keywords. In the following, we will refer to this latter group simply as “skills”.

In the second step, we follow a similar strategy as in Arntz, Böhm, Graetz, Gregory, Lehmer & Lipowski (2024), and use ChatGPT to generate contextual descriptions for each skill and supplement these descriptions with example occupations. Both of these pieces of information are aimed at providing more context on the specific skills in order to to enhance the quality of the ensuing classification into overarching skill groups. For example, the German job task “betreuen” can be used in the context of serving professional clients (then NR interactive) or in the context of, say, caretaking of the elderly (then NR manual). Adding job descriptions and example occupations helps distinguishing between related, but (in our view) different skill requirements.

Table OA2: Skill Classification and Example Occupations

Skill	**Group**	**Skill Description**	**Example Occupation**
Data Analysis	nrc	Analyzing data to extract meaningful insights for decision-making.	Data Analyst
Commercial Law	nrc	Applying laws and regulations related to commerce.	Commercial Lawyer
Financial Advisory	nri	Providing investment and financial planning advice.	Financial Advisor
Private Tutoring	nri	Teaching individuals in a one-on-one setting.	Tutor
Carpentry	nrm	Crafting wood structures and components for buildings.	Carpenter
International Cuisine	nrm	Cooking international cuisine.	Chef
Hardware installation	rc	Setting up and configuring hardware systems.	Hardware Installer
HR Administration	rc	Managing administrative HR tasks.	HR Administrator
Sheet Metal Fabrication	rm	Fabricating metal sheets into various shapes and products.	Metal Fabricator
Warehouse Work	rm	Performing tasks related to warehouse operations.	Warehouse Worker

Third, we classify skills into five well-established categories from the literature: non-routine (NR) cognitive, NR interactive, routine (R) cognitive, R manual, and NR manual. To accommodate this classification task, we ask ChatGPT to categorize skills, building upon explicit decision rules outlined in Dengler, Matthes & Paulus (2014). Our classification procedure is iterative meaning that the initial AI-generated classification is sequentially validated by research assistants and the project team to address ambiguities and make human decisions on edge cases. We manually reclassified approximately 13% of skill requirements, with the most challenging cases typically involving IT-related activities with varying degrees of repetitiveness and activities involving lots of personal interactions. For example, more repetitive activities such as IT-admin are considered routine cognitive, while more complex activities are considered NR cognitive. Similarly, activities with many personal interactions in the business context are typically classified as NR interactive, while activities with many personal interactions in the hospitality and health sector are often classified as NR manual.

In the fourth step, we perform various linguistic adjustments to reflect the terminology used in real-life job postings. This step is essential to ensure that our set of keywords captures the linguistic diversity seen in job postings.[7]

Our final dataset includes approximately 9,500 unique keywords, providing a conceptually and linguistically broad representation of non-AI skill requirements. Our comprehensive keyword list thus captures the breadth of skill demanded (how many conceptually distinct skills) as well as depth of conceptually identical skill terminologies.

To lend credence to our classification, we perform external validity by comparing our skills to the IAB Occupational Panel (Grienberger, Janser & Lehmer 2023). This data provides information on the occupation-level task structure, which is likewise based on BERUFENET. Because of the same underlying data source, we view this comparison as informative on the validity of our classification procedure. To operationalize these comparisons, we construct task intensity measures S_{io}, i.e. the definition of the task structure provided in the IAB Occupational Panel:

[7] It is important to point out that BERUFENET was not created to accommodate data preparation suitable for the analysis of job vacancies or related text data. Instead, BERUFENET is aimed at being an informative source for job seekers, commonly displayed by formal, noun-based descriptions (e.g., "development" of something), while job postings often use verb forms (e.g., applicants must "develop" something). To bridge this semantic gap, we systematically include both, noun and verb forms in our keyword lists. Moreover, we address compound skills that BERUFENET often combines using hyphens (e.g., Investment-/Financial advice). Firms do not always use this compound strucure, often instead opting for more specific requirements (financial advice and/or investment advice). Combining such compound skill requirements with separate entries therefore enhances the precision of our search algorithm.

$$S_{io} = \frac{\text{Number of skills j demanded in occupation o}}{\text{Total number of skills demanded in occupation o}} \tag{8}$$

where $j = 1, ..., 5$ represents the five skill groups defined above. This definition implies (i) $S_{ijlmt} \in [0, 1]$ $\forall j$ and (ii) $\sum_J S_{ijlmt} = 1$, thus describing the average relative importance of each skill j in vacancies posted by firm i. For example, $S_{NRI,ilmt} = 0.5$ implies 50% of all skills demanded in occupation o are interactive. Using these variables, we perform two exercises for external comparisons.

First, we correlate above skill measures from our OJV data with those from the IAB Occupational Panel (Table OA3). Overall, we find a a strong alignment across most skill categories. Especially our measures for NR cognitive and NR interactive activities display high correlations, each with a correlation coefficient of 0.75. Our measures for routine manual and NR manual likewise display high degrees of correlation with correlation coefficients of 0.69 and 0.59, respectively. For routine cognitive activities we also find substantial correlation on the order of 0.50. Taken together, these comparisons provide strong evidence on the validity of our classification procedure. Note, that imperfect correlation is expected as our measures also contain within-occupation heterogeneity in the task structure, which is not the case for the measures taken from the IAB Occupational Panel.

Table OA3: Correlation between OJV skills & IAB Occupational Panel: Occupational Task Structure

	OJV data				
	NRC	NRI	RC	RM	NRM
IAB Panel					
NRC	0.75				
NRI		0.75			
RC			0.50		
RM				0.69	
NRM					0.59

Second, we use indicators from the IAB data on the substitution potential (SP) of occupations (Dengler & Matthes 2018). The SP captures how easily tasks within an occupation can be automated by new technologies. Positive correlations indicate higher substitutability, while negative correlations suggest complementarities with technological adoption. Table OA4 shows that both of our routine measures display positive correlations with the SP indicators on the order of 0.40 - 0.45. These findings are consistent with insights from the vast polarization literature (Autor, Levy & Murnane 2003), implying that more repetitive tasks are more prone to substitution by technologies. In contrast, NR cognitive (-0.36) and NR interactive (-0.33) activities display negative correlations, consistent with the notion of complementarities between cognitively demanding tasks and technologies. Lastly, NR manual activities show a weak positive correlation (0.15), reflecting more limited SP compared to routine tasks, but also more limited complementarities (due to, typically, lower complexity compared to the other NR activities).

Table OA4: Correlation between OJV skills & IAB Occupational Panel: Substitution Potential

	OJV data				
	NRC	NRI	RC	RM	NRM
IAB Panel					
NRC	-0.36				
NRI		-0.33			
RC			0.40		
RM				0.45	
NRM					0.15