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Paying More, Asking More: Minimum Wages and the Skill Content of Labor Demand

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Paying More, Asking More: Minimum Wages and the Skill Content of Labor Demand*

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Abstract

In October 2022, Germany raised its statutory minimum wage from €9.82 to €12.00, an increase of more than 20 percent in a single year. Research on the reform has focused on wages, hours, and employment, but firms may also change what they ask of new hires. I examine whether more exposed occupations changed their skill demand more strongly after the reform, in the quantity, diversity, and composition of the skills requested. Combining administrative wage data from the German Earnings Survey with 5.8 million online job vacancies, I measure each occupation-region cell's exposure from the pre-reform wage distribution and extract the skills firms request from the vacancy texts. In a difference-in-differences design, more exposed cells request more skills per vacancy after the reform, concentrated in cognitive and manual requirements. The added demand falls on skills already central to the occupation rather than on a wider range, as the diversity of skills requested remains unchanged. Demand also shifts toward cognitive skills and away from soft ones. At the lower end, helper postings increasingly ask for skills typical of skilled-worker jobs. The effects are small but robust, and concentrated in the most exposed occupation-region cells.

Keywords: minimum wage, online job vacancies, tasks

JEL Codes: J23, J24, J31, J38

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1 Introduction

In October 2022, Germany implemented one of the most substantial minimum wage increases in its history. The statutory minimum wage rose from €9.82 to €12.00, corresponding to an increase of more than 20 percent within a single year (Dütsch et al. 2025). This adjustment stands in stark contrast to the few-cent annual steps that had followed the introduction of the minimum wage at €8.50 in 2015 (Dütsch et al. 2025). Given its magnitude, the reform has triggered a growing body of research examining its effect on wages, working hours and employment.[1]

So far, this literature has largely focused on conventional labor market outcomes. Much less is known about whether firms also respond to minimum wage increases by changing the task content of the jobs they seek to fill. A binding minimum wage raises the cost per worker and tightens firms' budget constraints (e.g. Borjas 2015; Manning 2003), which may lead firms to reorganize production, reallocate tasks across workers, or increase the range and complexity of tasks assigned to each worker (Acemoglu & Autor 2011; Lazear 2000). Even in the absence of strong employment effects, firms may therefore demand broader skill sets and greater versatility from new hires (Autor 2013; Goos et al. 2014). Focusing only on wages, working hours, and employment may thus overlook an important dimension of firm adjustment: changes in the skill content of labor demand. This constitutes an important gap in the literature on the effects of the increase.

I examine this adjustment margin by estimating how the 2022 minimum wage increase changed the skill content of labor demand, measuring its effect on the quantity, diversity, incidence, and composition of the skills that firms request from new hires. This shifts the focus from the number and kind of postings firms place to what they ask for inside them. I define a set of skill keywords grouped into four categories (cognitive, digital, manual, and soft), broadly following Deming & Kahn (2018), and use them to extract the requested skills from the full text of 5.8 million online job vacancies covering April 2022 to December 2023. I combine these vacancies with high-quality administrative wage data from the

[1] See, for instance, Bossler, Chittka & Schank (2026), Bachmann et al. (2026), and Bossler, Liang & Schank (2026) for recent evidence on the effects of the 2022 minimum wage increase on wages, working hours, and employment.

German Earnings Survey. From the wage data I construct two measures of pre-reform minimum wage exposure, which I merge to the skill outcomes at the occupation-region level. In a difference-in-differences design that exploits differential treatment intensity across occupation-region cells, I then assess whether more exposed cells adjust their skill demand more strongly after the reform.

The results reveal a modest but robust increase in the quantity of skills that firms request after the reform. More exposed occupation–region cells list more skill requirements per vacancy, with the increase concentrated in cognitive and manual skills. Digital and soft skills, by contrast, are largely unaffected. This adjustment reflects greater intensity rather than greater variety. The number of distinct skills requested within a cell does not increase, suggesting that firms ask more often for skills already associated with the occupation rather than expanding the set of requirements. The same pattern carries into the other two outcomes. The incidence of manual skills, so the share of postings in which they appear, rises while soft skills become less prevalent. At the same time, the composition of skill demand shifts away from soft skills and toward cognitive skills.

I then examine two mechanisms behind this adjustment. The first is skill concentration. For each occupation, I identify the skills that account for the bulk of pre-reform skill mentions and label them as core skills, while rarer and more peripheral requirements are classified as satellite skills. After the reform, the share of core skills rises in more exposed cells. The increase in skill demand therefore appears to be concentrated in requirements already central to the occupation rather than in more peripheral skills. The second mechanism is skill upgrading. Among helper-level vacancies, more exposed employers increasingly request skills typically associated with skilled-worker positions. This points to a modest increase in the complexity of requirements at the bottom of the occupational hierarchy.

The findings are robust across a range of specifications. Event-study estimates show little evidence of differential pre-trends, and the results are similar when using different exposure measures, alternative regional aggregations, and a posting-level specification. The effects are concentrated in the most exposed cells, with no comparable response

among cells where the reform did not bind. Importantly, the reform does not appear to change the posting behavior of firms. I find no significant effects on the number of postings or on the requirement-level composition of advertised jobs, in line with Dorau et al. (2025). This suggests that the adjustment occurs within postings, through the skills firms request, rather than through changes in the volume or broad composition of vacancies.

This paper contributes to the literature on the labor-market effects of the minimum wage in three ways. First, I extend the set of outcomes to the task content of labor demand. Existing work on the German minimum wage, including the 2022 increase, has mainly studied wages, working hours, employment, and vacancy volumes. Wage effects are consistently positive at the lower end of the distribution (e.g. Burauel et al. 2020; Caliendo et al. 2023; Dustmann et al. 2022; Ahlfeldt et al. 2018; Bachmann et al. 2022; Bossler, Chittka & Schank 2026). The evidence on working hours is mixed, with some studies finding short-run reductions (Bossler & Gerner 2020; Ohlert 2025) and others no significant change (Biewen et al. 2022; Bossler, Chittka & Schank 2026). Reductions in hours can also attenuate the effect on monthly earnings, which stay comparatively stable despite rising hourly wages (Bachmann et al. 2025). Employment effects are generally small or absent in the aggregate (Ahlfeldt et al. 2018; Bossler & Schank 2023; Dustmann et al. 2022; Garloff 2019), with modest declines confined to marginal employment (Bossler & Gerner 2020; Caliendo et al. 2018; Bossler, Liang & Schank 2026). While this evidence provides a detailed picture of conventional labor-market margins, it says little about whether firms also change the content of the jobs they seek to fill. One reason this margin has received little attention is that skill adjustments are hard to measure in administrative data.

This margin becomes observable, however, through online job vacancy data, which record the skills firms seek at the hiring stage and are now widely used in labor economics (e.g. Deming & Kahn 2018; Hershbein & Kahn 2018). Their application to minimum wage research remains limited, and the existing studies focus on the postings themselves rather than their content. Kudlyak et al. (2025) find that minimum wage increases reduce

the number of US postings in low-wage occupations, and Adams-Prassl et al. (2020) show that UK increases raise the share of flexible and non-salaried vacancies. Closest to this paper, Dorau et al. (2025) study the 2022 German increase with vacancy data and find no significant change in posting volumes, educational requirements, or contract types. I move the analysis inside the posting, to the skills firms request, and show that the task content of labor demand responds even where these coarser posting characteristics do not.

Second, I examine the mechanism behind this adjustment and identify it as a consolidation of existing skill demand. A small literature shows that firms facing higher labor costs respond by reorganizing production and raising work intensity. Hirsch et al. (2015) document cross-training, multitasking, and tighter scheduling in the fast-food sector, and Coviello et al. (2022) and Ku (2022) find corresponding gains in worker productivity. This evidence is indirect, inferred from output or productivity rather than observed in the tasks themselves. To the best of my knowledge, I am the first to apply a core-satellite distinction in the minimum wage context, separating an occupation's core skills, those central to it and accounting for the bulk of its skill mentions, from its rarer satellite skills. The added demand concentrates on core skills, which identifies the adjustment as an intensification of existing requirements rather than a broadening of skill profiles.

Third, I document a narrow form of skill upgrading at the bottom of the job-complexity ladder. A substantial literature finds that firms facing a higher wage floor substitute toward more productive or higher-skilled workers. Giuliano (2013), using firm personnel data, finds that higher minimum wages raised the relative employment of teenagers, a substitution across worker groups partly driven by the larger and higher-quality pool of teenage applicants the increase drew in. Horton (2025), randomizing minimum wages in an online labor market, shows that treated firms shift toward more productive hires. For Germany, Dustmann et al. (2022) find that the minimum wage reallocates workers toward more productive firms. Closest to my setting, Clemens et al. (2021) use US vacancy data and show that minimum wage increases raise the education requirements firms post in low-wage occupations. Across these settings upgrading either appears in who is hired or

in coarse posting requirements such as a high-school diploma. I show that it also operates within the skill content of low-wage vacancies: more exposed employers advertising helper positions increasingly request skills typically associated with skilled-worker jobs, upgrading the requirements attached to otherwise low-wage postings rather than only the workers who fill them.

Taken together, these findings carry social and economic implications. If firms meet a higher wage floor by asking more of each hire, entry into low-wage work can become harder for the least experienced and least qualified applicants. At the same time, workloads in exposed positions may rise, falling on workers already at the bottom of the wage distribution. Adjustments of this kind take place inside the jobs and therefore persist even where aggregate employment does not move. Accounting for these within-job adjustments therefore matters both for policymakers setting the minimum wage and for researchers evaluating it.

The remainder of the paper is structured as follows. Section 2 describes the wage and online job vacancy data, the construction of the exposure measures, and the definition of the outcome variables that capture firms' skill demand. Section 3 sets out the empirical strategy. Section 4 presents the main results and robustness checks, Section 5 examines the mechanisms behind them, and Section 6 concludes.

2 Data and Descriptives

The empirical analysis combines two complementary data sources. The first dataset is the German Earnings Survey (ES) (Finke et al. 2023), which provides detailed administrative information on employment and wages. It is used to construct the exposure measures to the minimum wage. The second data source consists of online job vacancy (OJV) data, which allow me to observe the content of labor demand at a high frequency. I construct the outcome variables from the vacancy texts by extracting the number and type of skills requested by firms. These measures capture how the task content of labor demand changes in response to the minimum wage increase.

2.1 Wage Data

The ES is a high-quality administrative employer–employee dataset collected by the German statistical offices (Destatis 2025). Participation is mandatory for firms, as the survey is used for official statistics.[2] The ES is based on a representative sample of approximately 60,000 establishments, that are required to report detailed information on wages and working hours for all their employees (Finke et al. 2023). This results in a large dataset, covering more than 8 million workers in 2022. As the reported information is typically drawn directly from firms' payroll and accounting systems, the data are considered highly accurate and reliable (Bossler, Chittka & Schank 2026).

The ES records gross monthly earnings and contractual working hours for each employee in April 2022. I construct hourly wages as monthly earnings divided by weekly working hours multiplied by 4.345, following (Bachmann et al. 2025). Importantly, the collection of the survey precedes the two-step increase of the statutory minimum wage in 2022—from €9.82 to €10.45 in July and to €12 in October—such that the constructed wage measure is not directly affected by these policy changes.

Beyond wage information, the ES also contains detailed regional identifiers based on the firm's official municipality code (Amtlicher Gemeindeschlüssel, AGS). To capture economically meaningful labor markets, I aggregate municipalities into 141 labor market regions (LMR) following Kosfeld & Werner (2012). This aggregation accounts for commuting patterns and reflects functional labor markets that extend beyond administrative boundaries. The resulting level of geographical detail allows me to exploit substantial regional variation in the empirical analysis.

In addition to regional variation, the analysis also exploits occupational heterogeneity. The ES provides detailed occupation codes for each employee based on the German Classification of Occupations 2010 (Statistik der Bundesagentur für Arbeit 2021), which is available at the 8-digit level. As the full 8-digit classification is highly granular and leads to substantial sparsity in the data, I focus on a more aggregated level. Specifically, I construct occupation cells based on 3-digit occupational groups which capture broad

[2] If a firm is selected for the survey, it is legally required under §4 of the German Earnings Statistics Act (Verdienststatistikgesetz) to provide current information on wages and working hours.

occupational categories, and combine them with the 5th digit of the KldB classification. This digit reflects the requirement level of an occupation, distinguishing between four categories: helper, skilled worker, specialist and expert. This approach allows me to retain meaningful variation in occupational skill requirements while ensuring a sufficient number of observations within each cell.

I restrict the sample by excluding workers who are not subject to the statutory minimum wage, namely apprentices, interns, and workers below the age of 18. In addition, the ES contains observations derived from the public service statistics as well as imputed information for establishments without employees subject to social security contributions.[3] Since these observations are not directly comparable to the core data, I exclude them from the analysis.

Due to data protection regulations, cells with fewer than three observations are suppressed by the statistical offices. I therefore exclude all cells that do not meet this requirement. This constraint primarily affects the most disaggregated specifications that combine occupational and regional variation. At this level, approximately 7,000 cells are removed from an initial sample of around 40,000. This reduction is however unlikely to affect the results, as the excluded cells correspond to very small and infrequent occupation–region combinations, which are also unlikely to exhibit meaningful job posting activity in the vacancy data.

2.2 Measuring Minimum Wage Exposure

Since the reform raised a uniform national wage floor, it did not generate exposure variation directly. I therefore identify its effects by measuring how strongly different parts of the labor market were bound by the new threshold. I construct exposure measures from the pre-reform wage distribution, exploiting the fact that occupations and regions differed markedly in the share of workers earning close to the minimum wage before October 2022.

[3]Information on public service sector employees is collected separately through the public service statistics and subsequently merged into the Earnings Survey. Given its origin from a different data source and potentially differing data collection procedures, these observations are excluded from the analysis. Moreover, as public sector wages are largely determined by collective agreements, their exclusion is unlikely to affect the measurement of minimum wage exposure.

I measure exposure at the level of occupation-by-region cells, defined by the occupation and labor market region classifications introduced above. The baseline specification combines labor market regions with occupation cells at the 3-digit-plus-requirement-level, which is granular enough to isolate the low-wage segments where the reform bound most tightly. I also construct exposure at coarser levels of aggregation, which serve as robustness specifications. At the regional dimension, I consider two further levels in addition to labor market regions: the federal-state and national levels. The national level abstracts from spatial heterogeneity and isolates purely occupational variation, which I use only in the descriptives. The state level allows me to apply the survey weights that render the Earnings Survey representative for the whole of Germany. At the occupational dimension I additionally use the coarser 3-digit groups, which place more workers in each cell and are therefore less affected by data protection restrictions. This coarser aggregation is also required for the parts of the analysis in which the within-occupation requirement level serves as the outcome: since the fifth KldB digit then defines the dependent variable, exposure must be measured at the 3-digit level, which pools across requirement levels.

The first exposure measure, the *bite*, captures the incidence of the reform. It is defined as the share of workers in a cell whose pre-reform wage lay below the new statutory minimum wage:

$$bite_{or} = \frac{1}{N_{or}} \sum_{i \in (o,r)} \mathbf{1}\big(w_i^{\text{pre}} < w^{\text{MW}}\big)\,, \tag{1}$$

where i indexes workers, o the occupation, and r the region; N_{or} is the number of workers in cell (o, r), w_i^{pre} is the worker's pre-reform hourly wage, and $w^{\text{MW}} = €12$ is the new floor. The bite thus records what fraction of workers in a cell were directly affected, but not the extent to which their wages fell below the new minimum.

The second measure, the *gap*, also captures the intensity of exposure. It is the aggregate wage shortfall relative to the new minimum wage, expressed as a fraction of the cell's total wage bill:

$$gap_{or} = \frac{\sum_{i \in (o,r)} \max\big\{0,\ w^{\text{MW}} - w_i^{\text{pre}}\big\}}{\sum_{i \in (o,r)} w_i^{\text{pre}}}. \tag{2}$$

The operator $\max\{0, \cdot\}$ ensures that only workers below the new floor enter the numerator, which measures the total pay increase required to bring every worker in the cell up to the new minimum wage floor. Normalizing by the pre-reform wage bill yields a measure comparable across cells of different size and pay level. The gap thus captures the depth of the shortfall, not just its incidence.

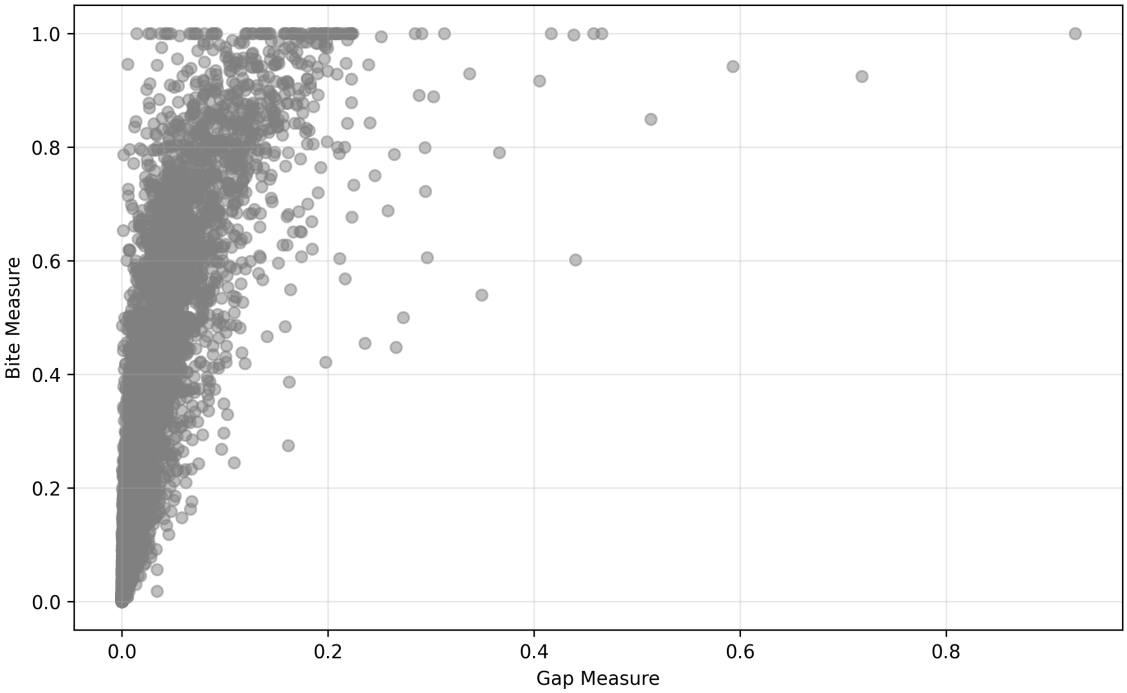
The two measures capture related but distinct dimensions of exposure. Figure 1 plots them against each other across occupation-by-region cells at the baseline level of aggregation (LMR and 3-digit-plus-requirement-level). They are strongly and positively correlated, with a correlation coefficient of 0.8: cells with a larger share of affected workers also tend to face a larger aggregate wage shortfall. The two measures nonetheless differ systematically in magnitude. Many cells display bite values close to one while having substantially smaller gap values. This reflects the difference between the incidence and the depth of exposure. In such cells, a large share of workers earned below the new minimum wage, leading to a high bite. However, if these workers were only slightly below the threshold, the required increase in the wage bill remains modest, resulting in a comparatively small gap.

Table B1 in the Appendix lists the ten most exposed occupations. Exposure is ranked at the national level, which abstracts from idiosyncratic occupation–region cells in small local labor markets, and weighted by employment.[4] The two measures select broadly the same occupations, though their exact ordering differs. Exposure is concentrated in cleaning services, gastronomy and food preparation, and low-skilled retail and logistics occupations. In the most affected of these, more than half of all workers earned below €12 before the reform according to the bite. Consistent with the pattern in Figure 1, the corresponding gap values are considerably smaller in magnitude.

Aggregating exposure to the regional level reveals pronounced spatial variation. Figure 2 maps employment-weighted average gap exposure across labor market regions, where each region's exposure is the average across its occupation cells weighted by cell

[4]Employment counts are taken from the IAB occupational panel (Grienberger et al. 2023), which reports head counts in 2022 by 3-digit-plus-requirement-level occupation and can therefore be merged directly onto the exposure measures.

Figure 1: Scatterplot for Bite vs. Gap

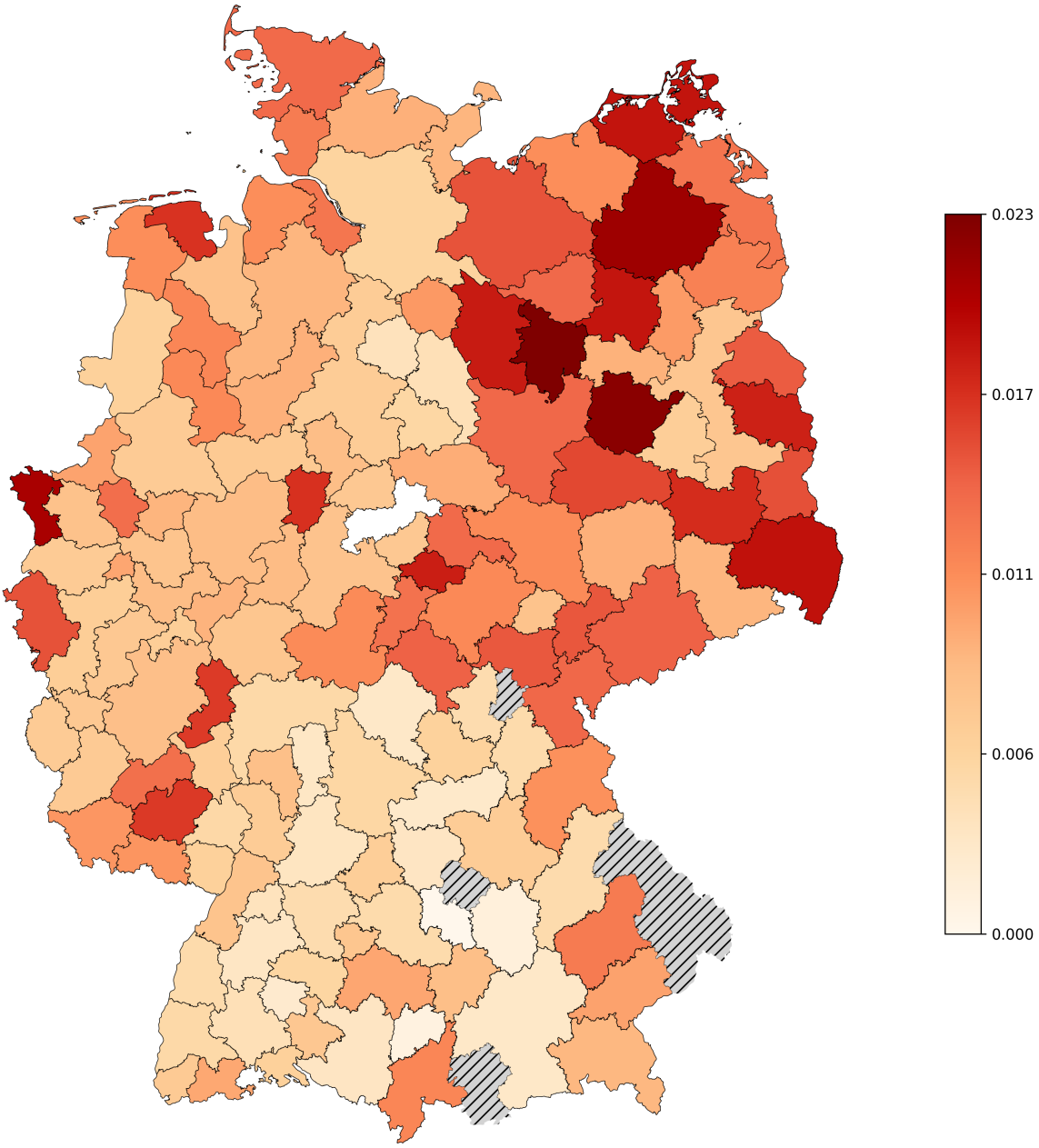


Notes: Every dot represents an occupation-region cell.
Source: German Earnings Survey, own calculation.

employment. The bite map yields a very similar picture and is presented in Appendix Figure A1. Exposure is substantially higher in eastern than in western Germany, mirroring the persistently lower wage levels in the East; a pattern which is well documented in the German minimum wage literature (Dütsch et al. 2025). At the same time, several western regions exhibit high exposure, so minimum wage relevance is not confined to the East, while exposure is generally lowest in the industrial, higher-wage regions of the South.

Taken together, the descriptive evidence shows that exposure to the 2022 reform varied substantially across both occupations and regions. This variation is the source of identification exploited in the empirical analysis. The bite and gap measures capture closely related dimensions of that variation and are strongly correlated, but differ in their emphasis: the bite reflects the share of workers exposed, while the gap reflects the extent of their exposure.

Figure 2: Regional Dimension of Gap Exposure



Notes: Average gap exposure per labor-market region in April 2022. Darker colors indicate a higher exposure.[a]
Source: German earnings survey, own calculation.

[a]Greyed-out regions were censored due to data protection regulations by the statistical office. As these regions account for only a small share of the sample, this should not affect the main results.

2.3 Online Job Vacancy Data & Descriptives

To complement the administrative data, I draw on a large-scale dataset of online job vacancies (OJVs) provided by Palturai GmbH and its subsidiary Finbot AG. Whereas the ES provides information on the wages and working hours of incumbent workers, the vacancy data capture labor demand at the hiring stage. They reveal which skills and tasks firms seek in prospective workers and therefore provide a direct, forward-looking measure of the task content of labor demand. This margin is generally not observable in administrative data on incumbent workers.

The OJV data comprise daily job postings advertised online in Germany between 2017 and 2025, aggregated from a broad range of sources, including firm career pages, major job boards, temporary employment agencies, and digital recruitment platforms. In scope and coverage the dataset is comparable to widely used commercial vacancy data such as Lightcast or Indeed. Postings are collected through a continuous web-scraping process that monitors these sources daily, so that newly advertised vacancies enter the data in near real time. Prior to delivery, the raw data undergo initial preprocessing, including standard cleaning procedures and the removal of duplicate postings within sources. Building on this, additional in-house processing steps are conducted to prepare the data for empirical analysis. These include standard text preprocessing techniques following Gentzkow et al. (2019) and Ash & Hansen (2023), as well as the classification of vacancies by occupation and region.

Having full access to the vacancy texts allows me to draw directly on the underlying raw information contained in job ads and enables the construction of tailored text-based measures. To improve the precision of the task extraction, each vacancy is partitioned into functionally distinct text segments through a zoning procedure. This segmentation facilitates the identification of job tasks by separating them from other components of the job advertisement, such as firm descriptions, benefit section, or application instructions.

For the main analysis I restrict the sample to vacancies posted between April 2022 and December 2023. The starting point is chosen for two reasons. First, it provides six months of pre-reform observations against which to assess differential trends before the

October 2022 increase. Second, it aligns the vacancy data with the wage data, as the Earnings Survey is likewise conducted in April. I follow the postings through to the end of 2023 in order to trace the adjustment to the reform over a sufficiently long post-period, while stopping in December 2023 to avoid contamination from the subsequent minimum wage increase in January 2024. This leaves a total of 5.8 million postings in the estimation sample for April 2022 to December 2023. Parts of the mechanism analysis in Section 5 instead draw on the full history of the data: to construct pre-reform skill vectors, I use all postings from 2017 up to the start of the estimation window in April 2022.

To extract task demand from the vacancy texts, I follow a keyword-based approach. I construct a comprehensive skill dictionary from the Federal Employment Agency's BERUFENET database, an occupational-information platform that provides detailed descriptions of occupations in Germany, including structured information on the skills typically required in each occupation. I extract these skill descriptions across all occupations and consolidate them into a single dictionary. The resulting taxonomy comprises more than 8,000 distinct skills and forms the basis for identifying task requirements in the vacancy texts. A posting is coded as demanding a given skill whenever the corresponding keyword appears in its text.

For the analysis I group these skills into four broad categories according to their underlying nature — cognitive, digital, manual, and soft skills — following Benner et al. (2026). The four groups are motivated by the general nature of the tasks to be performed and broadly consolidate distinctions drawn in the existing literature. Deming & Kahn (2018), for instance, use a similar approach in which they classify job-ad keywords into ten groups: my cognitive category is analogous to theirs, my digital category relates to their computer and software skills, and my soft-skill category subsumes their social, character, and customer-service skills. Their scheme contains no manual category, as they study professional occupations; in my setting an explicit manual category is essential, since the occupations most exposed to the minimum wage are concentrated at the lower end of the wage distribution, where physical and routine manual tasks are common. This grouping is also close to the task-based approach of Acemoglu & Autor (2011), who characterize

jobs as bundles of cognitive and manual tasks. Appendix Figure A2 provides an overview of the most frequent skill keywords assigned to each of the four skill categories using word clouds.

2.3.1 Outcome definition

Based on the keyword matches I construct four measures of skill demand, each defined at the occupation–region cell level. Each measure is calculated monthly, providing a time-varying outcome for every occupation–region cell. I index a vacancy by v within a cell (occupation o, region r, month t) and write N_{ort} for the total number of vacancies in that cell. Let $skills(v)$ be the total number of detected skills in vacancy v and $skills^c(v)$ the number of skills in a specific category $c \in \{\text{cognitive}, \text{digital}, \text{manual}, \text{soft}\}$. Summing up all skills across categories yields the total number of skills: $skills(v) = \sum_c skills^c(v)$.

The first measure, the *skill quantity*, captures the average number of skills listed per vacancy within an occupation–region cell, as defined in Equations 3 and 4. For each category it is the average number of skills per vacancy over the N_{ort} postings in the cell,

$$quantity^c_{ort} = \frac{1}{N_{ort}} \sum_{v \in (o,r,t)} skills^c(v), \tag{3}$$

and the overall quantity is the sum across categories,

$$quantity_{ort} = \sum_c quantity^c_{ort}. \tag{4}$$

The second measure, *skill diversity*, is defined in Equations 5 and 6. It captures the breadth of skill demand and is given by the number of different skills requested at least once in a given cell:

$$diversity^c_{ort} = |\bigcup_{v \in (o,r,t)} \mathcal{S}^c(v)|. \tag{5}$$

The union $\bigcup_{v \in (o,r,t)}$ pools the skills named across all vacancies in the cell, and because $\mathcal{S}^c(v)$ is a set, each skill is counted once, regardless of how many postings request it. The

total number of distinct skills in a cell is then the sum across categories,[5]

$$diversity_{ort} = \sum_{c} diversity^{c}_{ort}. \tag{6}$$

These two measures capture different margins of adjustment. The *skill quantity* in (4) can increase if individual vacancies list more skill requirements, even if the overall set of requested skills remains unchanged. By contrast, *skill diversity* in (6) increases only if employers demand a wider variety of competencies within the cell. An increase in this measure therefore indicates a broadening of skill demand, whereas a decline points to a more concentrated skill profile.

The next two measures serve a different purpose. The *skill quantity* and *skill diversity* are the primary outcomes, capturing the level and the breadth of demand. The *skill incidence* and *skill composition* instead help interpret them, showing how a change is distributed across postings and across skill categories within postings. Neither is an independent margin: a category demanded more intensively, or across a wider set of distinct skills, will also tend to appear in more postings and carry more weight in the overall skill composition. I therefore treat them as secondary to the primary two.

The *skill incidence* captures the extensive margin of demand for each skill category. It is given by Equation 7. For a given category, a vacancy is coded as one if it contains at least one corresponding skill requirement and zero otherwise. I average this indicator across all postings in a cell,

$$incidence^{c}_{ort} = \frac{1}{N_{ort}} \sum_{v \in (o,r,t)} \mathbf{1}\{skills^{c}(v) > 0\}. \tag{7}$$

The average in (7) gives the fraction of vacancies in the cell that request category c at all, so a higher value means the category has spread to more postings (e.g., if 5 of 10 postings in a cell request digital skills before the reform and 7 of 10 do afterwards, incidence rises from 0.5 to 0.7). The first two measures capture such a shift only indirectly, because both

[5]The four categories are mutually exclusive, so no keyword appears in more than one category and the per-category counts add up without overlap.

the *skill quantity* and the *skill diversity* can stay flat even as a category spreads to more postings. *Skill incidence* isolates that share directly.

The fourth measure, the *skill composition*, captures the relative importance of each skill category within a cell. It is defined in Equation 8 as the average share of a vacancy's detected skills that belong to a given category,

$$composition^{c}_{ort} = \frac{1}{N_{ort}} \sum_{v \in (o,r,t)} \frac{skills^{c}(v)}{skills(v)}, \tag{8}$$

For each vacancy, $skills^{c}(v)/skills(v)$ is the share of category c among all skills in the posting; if half of a posting's skills are cognitive, that share is 0.5, while another posting in the same cell might have a cognitive skill share of 0.4. Averaging these shares over the N_{ort} postings with $\frac{1}{N_{ort}} \sum_{v \in (o,r,t)}$ gives the relative importance of category c in the cell, so the two example postings contribute a cognitive composition of 0.45. The four category shares of a vacancy always sum to one, and so do the four cell averages. *Skill composition* therefore reflects the intensive margin of adjustment as it isolates changes in the skill mix, independently of how many skills are demanded overall.

2.3.2 Outcome descriptives

Table 1 provides an overview of the skill-based outcome variables before and after the minimum wage increase. The pre-reform period covers all observations from April to September 2022, while the post-reform period begins in October 2022 and extends to the end of 2023. The third column reports the difference between the two periods, with significance from a t-test on the equality of means.

Before the reform, the average online job vacancy contained slightly more than five skill requirements. Cognitive skills are the most frequently mentioned category, at around 2.3 mentions per vacancy, followed by manual and soft skills with roughly one mention each, while digital skills appear least often, in about every second vacancy. After the reform, the total number of skills is essentially unchanged. The categories move in opposite directions, however: manual skill mentions increase, digital and soft skill mentions de-

Table 1: Descriptive statistics of outcome variables

Outcome variable	Pre-Reform	Post-Reform	Difference
Skill quantity			
Total skills	5.116 (2.558)	5.112 (2.533)	-0.004
Cognitive skills	2.328 (1.817)	2.328 (1.787)	0.000
Digital skills	0.546 (1.068)	0.535 (1.042)	-0.011***
Manual skills	1.226 (1.459)	1.252 (1.482)	0.026***
Soft skills	1.017 (1.046)	0.997 (1.040)	-0.020***
Skill diversity			
Total skills	28.980 (46.310)	29.194 (44.718)	0.214
Cognitive skills	13.288 (22.016)	13.463 (21.634)	0.175**
Digital skills	4.493 (15.424)	4.348 (14.323)	-0.145***
Manual skills	5.929 (9.084)	6.168 (9.349)	0.239***
Soft skills	5.270 (8.259)	5.216 (8.049)	-0.055*
Skill incidence			
Cognitive skills	0.762 (0.330)	0.767 (0.323)	0.005***
Digital skills	0.244 (0.347)	0.242 (0.343)	-0.002*
Manual skills	0.516 (0.399)	0.521 (0.397)	0.005***
Soft skills	0.532 (0.378)	0.523 (0.378)	-0.009***
Skill composition			
Cognitive skills	0.416 (0.257)	0.418 (0.254)	0.002**
Digital skills	0.081 (0.144)	0.080 (0.142)	-0.001
Manual skills	0.254 (0.284)	0.257 (0.284)	0.003***
Soft skills	0.209 (0.222)	0.206 (0.220)	-0.003***
Observations	108,001	241,842	

Notes: Observations are cell-level (occupation × labor market region × month) over the estimation sample April 2022–December 2023. The table reports means with standard deviations in parentheses. The pre-reform period covers April–September 2022, the post-reform period October 2022–December 2023. The difference column reports post-reform minus pre-reform means, with significance from a two-sample t-test of equal means (unclustered). See Equations 3 to 8 for a definition of the outcome variables.

cline, and cognitive skill demand remains flat. Although these differences are statistically significant, their magnitudes are small.

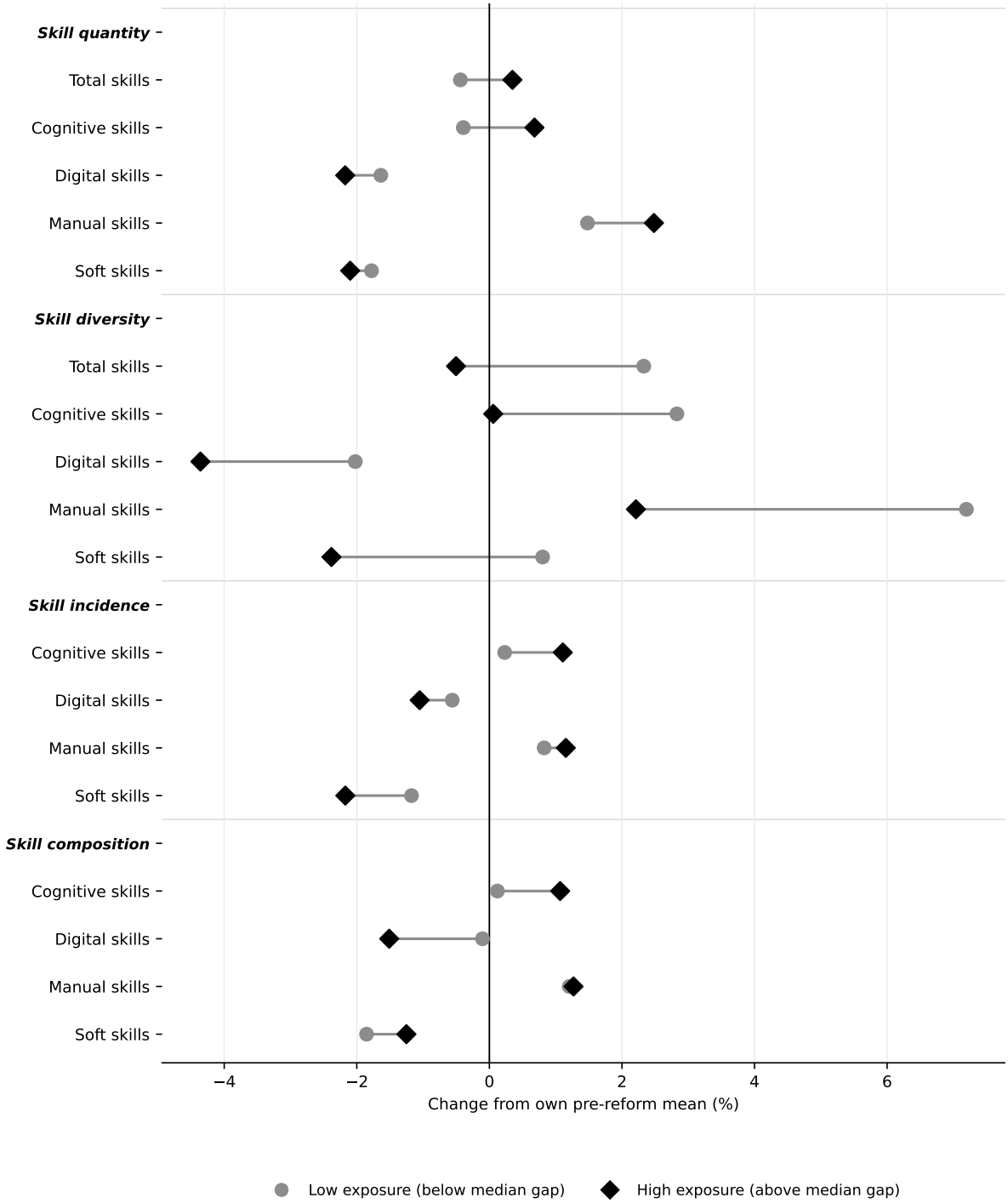
The second group of outcomes captures the number of distinct skills mentioned within an occupation–region cell in a given month. In the pre-reform period, a cell demands around 29 distinct skills on average, of which roughly thirteen are cognitive. After the reform, the total number of distinct skills is statistically unchanged, but the composition again shifts: cells request a wider variety of cognitive and manual skills and a narrower range of digital and soft skills.

The third group of outcomes describes the *skill incidence*, the share of postings mentioning at least one skill of a given category. Cognitive skills are near-ubiquitous, appearing in more than three quarters of all vacancies, while manual and soft skills each feature in just over half and digital skills in roughly a quarter. The reform shifts these shares only marginally: the share of postings requiring cognitive and manual skills rises, while the share requiring digital and, more markedly, soft skills falls.

The final group captures the *skill composition*, the relative importance of each category among all skill mentions in a given cell. The pattern mirrors the preceding results. The manual skill share rises and the soft skill share falls, both significantly, while the cognitive skill share increases marginally and the digital skill share is unchanged. Taken together, the descriptive evidence points to a modest reorientation of skill demand after the reform, toward manual and, more weakly, cognitive requirements and away from soft skills, though the magnitudes involved are consistently small.

One reason for the small aggregate changes documented above is that the table pools all postings, including those for high-wage occupations that should be unaffected by the reform. Averaging across these dilutes any adjustment concentrated in the more strongly exposed segments of the labor market. Figure 3 therefore splits the sample at the median of the gap measure and plots, for each outcome, the change from the pre- to the post-reform mean separately for low- and high-exposure cells. Changes are expressed relative to each group's own pre-reform mean, which makes them comparable across outcomes measured on very different scales.

Figure 3: Change in outcome variables conditional on exposure



Notes: The figure plots the change in each outcome from the pre-reform period (April–September 2022) to the post-reform period (October 2022–December 2023), expressed as a percentage of the group's own pre-reform mean. Cells are split at the median of the gap exposure measure into low- and high-exposure groups. Observations are occupation–labor-market-region–month cells; means are weighted by the number of postings per cell.

The split reveals heterogeneity that the pooled means conceal. The *skill quantity* falls slightly in low-exposure cells but rises in high-exposure ones, and the same gradient holds for cognitive and manual skills, both of which increase more strongly where exposure is high. Digital and soft skills decline in both groups, somewhat more so among the exposed. The rise in overall skill demand in exposed cells is thus driven entirely by cognitive and manual requirements.

The clearest contrast appears for the *skill diversity*. Low-exposure cells broaden their demand, requesting more unique skills overall and particularly more unique manual and cognitive skills. High-exposure cells do not: their total variety is flat to slightly negative, and while they too request more unique manual skills, the increase is roughly a third the size of that in the low-exposure group. Exposed employers therefore raise the number of skills they request without expanding the range of skills they draw on, whereas less exposed employers broaden their profiles.

The extensive margin via the *skill incidence* shows a consistent exposure gradient. In every category the change is larger in absolute terms among high-exposure cells: the share of postings mentioning cognitive or manual skills rises more, and the share mentioning digital or soft skills falls more. Although the magnitudes are modest, the direction of the differential is uniform across all four categories.

The *skill composition* which captures the intensive margin broadly echoes this pattern, with the relative weight of cognitive skills rising more strongly and that of digital skills falling more sharply in exposed cells. Manual intensity increases by a similar amount in both groups, and the decline in soft intensity is, if anything, somewhat smaller where exposure is high.

Overall, the descriptive comparison points to modest adjustments in skill demand after the minimum wage increase. The most exposed occupation–region cells appear to experience a slight increase in both the number and breadth of demanded skills, with the adjustment primarily driven by manual skill requirements. These changes are visible at both the extensive and intensive margins. At the same time, the economic magnitude of the differences remains small. The subsequent empirical analysis therefore examines

whether these descriptive patterns can be causally linked to the minimum wage increase.

3 Methodology

To estimate the causal effect of the 2022 minimum wage increase on firms' skill demand, I implement a difference-in-differences framework that exploits continuous variation in treatment intensity across occupation–region cells. Because the reform applied to all employees nationwide, there is no clean partition into treated and control units. The identifying variation instead comes from differences in the degree to which cells were bound by the new wage floor before it came into effect: if firms adjust their task demand in response to the higher minimum wage, more exposed cells should exhibit differential changes in skill requirements after the reform relative to less exposed cells.

The unit of observation is an occupation–region–month cell, with occupations defined at the 3-digit-plus-requirement-level and regions corresponding to labor-market regions. The outcome variable Y_{ort} denotes one of the skill-demand measures introduced in Section 2.3.1. Each outcome is constructed from the vacancy-level data and aggregated to the cell-month level, using the number of postings in a cell as weights. The baseline specification is:

$$Y_{ort} = \beta \left(\text{Exposure}_{or} \times \text{Post}_t \right) + \underbrace{\gamma_{o \times r}}_{\substack{\text{occupation} \\ \times \text{ region}}} + \underbrace{\lambda_{o \times t}}_{\substack{\text{occupation} \\ \times \text{ month}}} + \underbrace{\mu_{r \times t}}_{\substack{\text{region} \\ \times \text{ month}}} + \varepsilon_{ort} \tag{9}$$

where Exposure_{or} denotes the time-invariant exposure measure of occupation–region cell (o, r), and Post_t is an indicator equal to one from October 2022 onward. The specification includes occupation-by-region fixed effects, $\gamma_{o \times r}$, occupation-by-month fixed effects, $\lambda_{o \times t}$, and region-by-month fixed effects, $\mu_{r \times t}$.

The occupation-by-region fixed effects absorb all time-invariant differences in task demand across cells, whether across occupations or across labor markets within the same occupation. The occupation-by-month fixed effects control for shocks that affect all cells within an occupation in a given month, such as occupation-specific seasonality or na-

tionwide changes in occupational demand, for instance due to broad technology shocks such as the emergence of AI. Indeed, ChatGPT was launched in November 2022, only shortly after the minimum wage increase. Although its impact on the occupations most exposed to the minimum wage should be limited, since these are typically more focused on manual skills (see Appendix Table B1), it could nonetheless have shifted skill demand over the sample period. To the extent that such a technology shock affects skill demand uniformly within an occupation nationwide, it is absorbed by the occupation-by-month fixed effects $\lambda_{o\times t}$. The region-by-month fixed effects, included in some specifications, additionally absorb local labor-market shocks such as region-specific demand conditions and seasonal hiring patterns. Net of these fixed effects, the coefficient of interest β measures the differential change in skill demand after the minimum wage increase in more versus less exposed cells. Since the exposure measure ranges from zero to one, for ease of interpretation, I rescale it so that β reflects the effect of a one-percentage-point increase in exposure.

Because this fixed-effect structure progressively removes more of the identifying variation, I report a ladder of four specifications for the main results. All four include the cell fixed effect $\gamma_{o\times r}$ and differ in their time controls. Specification (1) is the least restrictive: it adds occupation-by-month fixed effects at the 3-digit KldB level, allowing broad occupational groups to follow their own monthly trajectories. Specification (2) adds region-by-month fixed effects. Specifications (3) and (4) mirror this pair but define the occupation-by-month effects at the finer 3-digit plus 5-digit KldB level, so that each detailed occupation follows its own path; specification (4) again adds the region-by-month effects.

Specification (4) is therefore the most conservative, as it saturates the fixed-effect structure most fully. My preferred specification is (2), which is slightly less restrictive. This choice is motivated by the subsequent analysis, where the requirement level—the fifth KldB digit—enters the outcome. Defining occupation-by-month fixed effects at the 5-digit level would absorb precisely this variation. I therefore focus on specification (2), which provides a rich set of controls, and report specification (4) alongside it wherever it

is applicable.

Observations are weighted by a fixed pre-reform cell weight, defined as the average number of postings in the cell over the pre-reform window of April to September 2022. Weighting by posting volume reflects that cell-level outcomes are averages over vacancies and are therefore measured more precisely in cells with more postings. Fixing the weight to the pre-reform period ensures that it does not itself respond to the reform, for instance through any effect of the minimum wage on posting activity, and so cannot induce a mechanical relationship between the weight and the outcome. Cells without postings in this window receive no weight and drop out of the estimation.

Standard errors are clustered at the labor market region level, allowing for arbitrary correlation in outcomes within a regional labor market over time. To keep the estimates comparable across the ladder, all specifications and outcomes are estimated on a common sample, defined by the observations retained under the most saturated specification.

To assess the parallel-trends assumption underlying the difference-in-differences design and to trace the dynamics of the adjustment, I complement the static estimates with an event-study specification. It replaces the single post interaction with a full set of interactions between exposure and indicators for each month relative to the reform:

$$Y_{ort} = \sum_{k \neq 0} \beta_k \left(\mathbf{1}\{t = k\} \times \text{Exposure}_{or} \right) + \gamma_{o \times r} + \lambda_{o \times t} + \mu_{r \times t} + \varepsilon_{ort}, \tag{10}$$

where k indexes event time relative to September 2022, the last month before the increase, which serves as the omitted reference period ($k = 0$). The pre-reform coefficients $\{\beta_k\}_{k<0}$ test whether more and less exposed cells were already on differential trends before the reform. The post-reform coefficients $\{\beta_k\}_{k>0}$ trace the timing and persistence of the adjustment.

I estimate the event study under my preferred specification (2), including occupation-by-region, 3-digit occupation-by-month, and region-by-month fixed effects. As a robustness check, I also use the most saturated specification (4).

4 Results

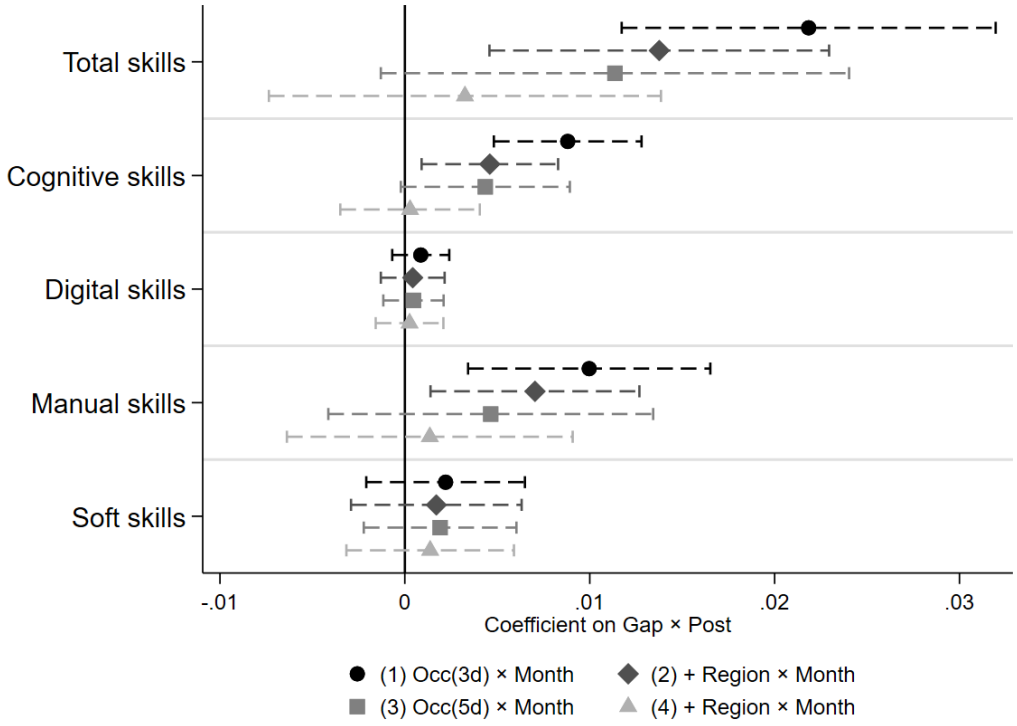
The results are presented in four steps, following the outcome measures introduced in Section 2.3: the *skill quantity*, *skill diversity*, *skill incidence* and *skill composition*. For each outcome, the figures plot the β coefficient on the interaction between minimum-wage exposure and the post-reform indicator across a ladder of fixed-effect specifications described in Section 3. I focus on Specification (2) as the preferred specification, while the remaining specifications illustrate the sensitivity of the estimates to alternative fixed-effect structures. Because exposure is measured in percentage points, the coefficients indicate the effect of a one-percentage-point increase in the gap measure.

4.1 DiD Results

Figure 4 reports the estimated effects on the average number of skill requirements per vacancy, the *skill quantity*. In the preferred specification, a one-percentage-point increase in the gap measure increases the total number of requested skills by approximately 0.014. This effect is statistically significant and indicates that more exposed occupation–region cells list more skill requirements per vacancy after the reform. However, the effect size is very modest as a one standard deviation increase in the gap measure (2.17) would only raise the task demand by about 0.03 skills per vacancy. Relative to the pre-reform average of around 5.1 skills per vacancy, this increase is small. Disaggregating total skill demand by category shows that the increase is concentrated in cognitive and manual skills. A one-percentage-point increase in the gap raises the number of cognitive skill mentions by around 0.005 and the number of manual skill mentions by around 0.007, while the estimated coefficients for digital and soft skills are smaller in magnitude and statistically insignificant across all specifications.

The magnitude of the estimates decreases as the fixed-effect structure becomes more saturated. The coefficients are largest in specification (1) and remain statistically significant for total, cognitive, and manual skill demand in the preferred specification (2). Under the more disaggregated specification (3), the effects on total and cognitive skills remain

Figure 4: Effect of gap exposure on *skill quantity*

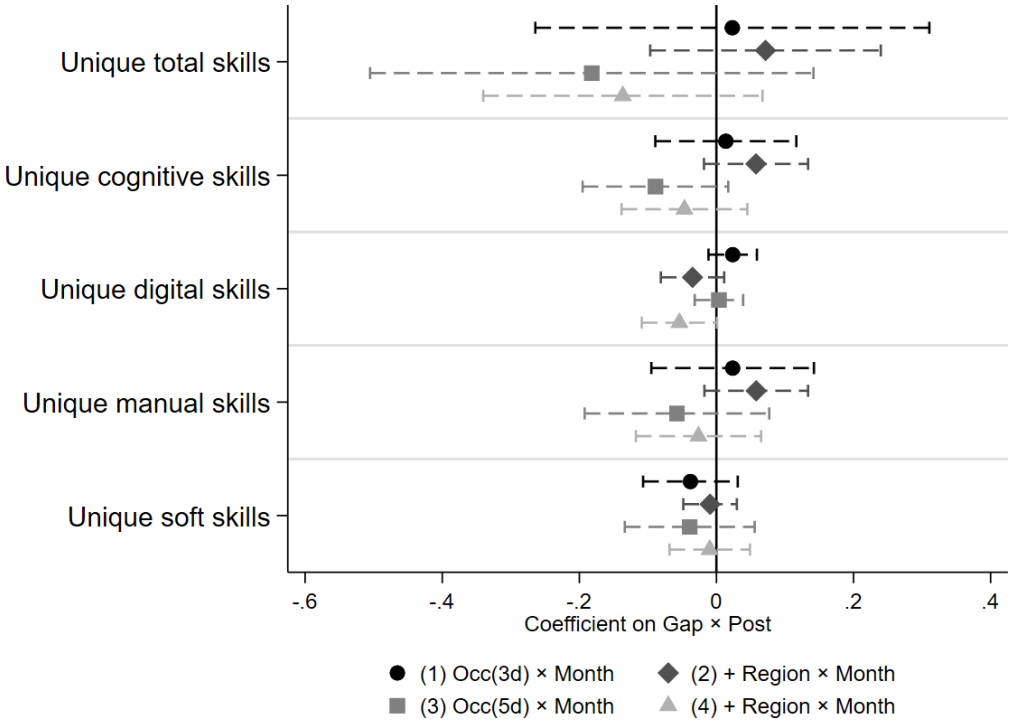


Notes: The figure reports coefficients on the interaction of the gap exposure measure with the post-October-2022 indicator, from separate regressions by outcome. Outcomes are the average number of skill mentions per vacancy in an occupation–labor-market-region cell. The gap is measured in percentage points. Specifications differ in their time controls, as indicated in the legend; all include occupation (5d) × labor-market-region fixed effects. Horizontal bars show 95 percent confidence intervals based on standard errors clustered at the labor-market-region level. N = 349,843.

significant at the 10% level, and in the most saturated specification (4) most coefficients are indistinguishable from zero. This attenuation is expected, given that specifications (3) and (4) absorb a large share of the identifying variation.

The increase in the number of skill mentions is not accompanied by a corresponding increase in the variety of skills demanded. Figure 5 reports the estimated effects on the *skill diversity*. In the first two specifications, none of the coefficients is statistically significant, indicating that more exposed cells do not request a broader set of skills after the reform. When the fixed-effect structure is further saturated by including 5-digit occupation-by-month effects, the estimated coefficients decrease and turn negative across skill categories, although they remain statistically insignificant.

Figure 5: Effect of gap exposure on *skill diversity*



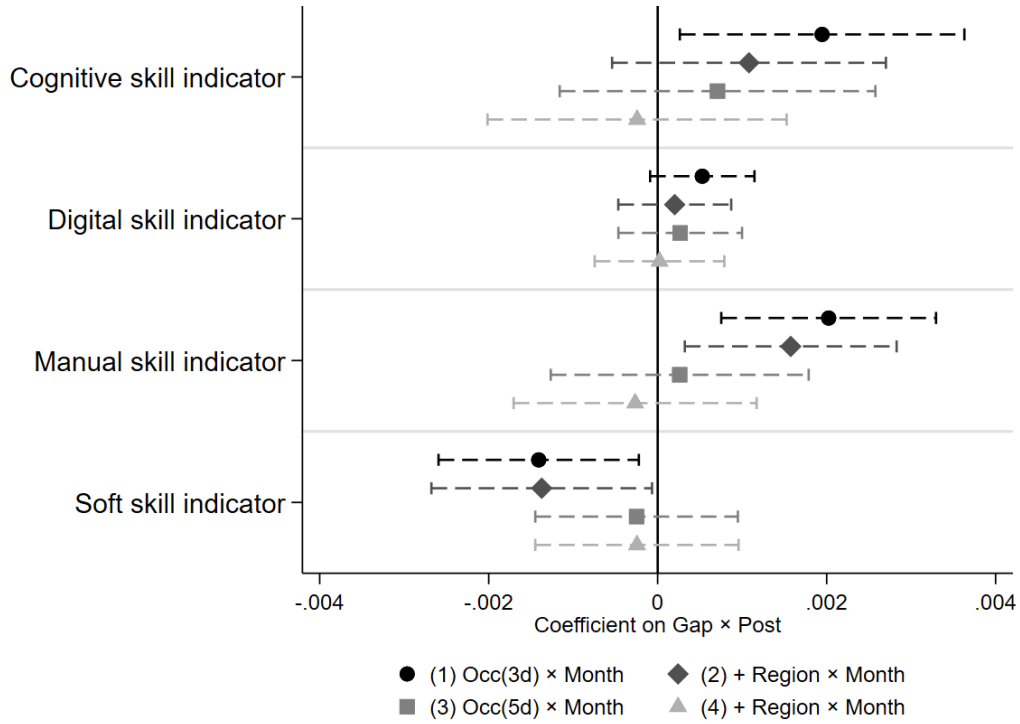
Notes: The figure reports coefficients on the interaction of the gap exposure measure with the post-October-2022 indicator, from separate regressions by outcome. Outcomes are the average number of unique skills per occupation–labor-market-region cell. The gap is measured in percentage points. Specifications differ in their time controls, as indicated in the legend; all include occupation (5d) × labor-market-region fixed effects. Horizontal bars show 95 percent confidence intervals based on standard errors clustered at the labor-market-region level. N = 349,843.

Taken together, Figures 4 and 5 suggest that the reform affected the intensity of skill demand rather than its breadth. More exposed cells appear to list more skill requirements

per vacancy, but these additional mentions do not translate into a wider range of distinct skills. The adjustment therefore seems to operate mainly through a more frequent mention of skills already demanded within the cell, rather than through an expansion of the overall skill portfolio.

While the previous results show changes in the quantity and diversity of skill mentions, these adjustments could still be driven by vacancies that already contained the respective skill requirements before the reform. To assess whether the minimum wage increase also affected how widely different skill categories appear across postings, I re-estimate equation (9) using the *skill incidence* outcome. This outcome is defined as the share of vacancies within an occupation–region–month cell that mention at least one skill from a given category. The results are shown in Figure 6.

Figure 6: Effect of gap exposure on *skill incidence*



Notes: The figure reports coefficients on the interaction of the gap exposure measure with the post-October-2022 indicator, from separate regressions by outcome. Outcomes are the share of postings in a cell that require at least one skill of the respective category. The gap is measured in percentage points. Specifications differ in their time controls, as indicated in the legend; all include occupation (5d) × labor-market-region fixed effects. Horizontal bars show 95 percent confidence intervals based on standard errors clustered at the labor-market-region level. N = 349,843.

The findings indicate that exposure raises the share of vacancies demanding manual

skills and lowers the share demanding soft skills. The cognitive-skill share is positive but not statistically significant in the preferred specification, reaching significance only under specification (1), and the digital-skill share is essentially unchanged throughout. The rise in manual skill demand documented above therefore operates in part on the extensive margin: more exposed cells not only request more manual skills per vacancy but also spread manual requirements across a larger share of their postings. Soft skills, by contrast, recede on this margin, appearing in fewer postings as exposure rises.

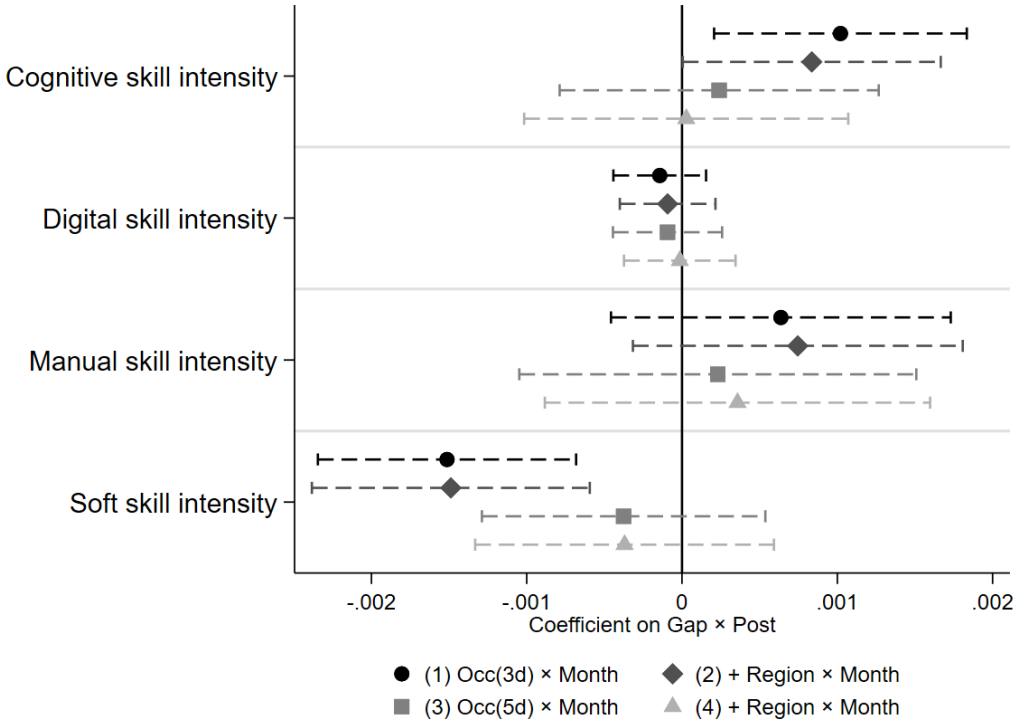
Similar to the results for skill counts, the estimated effects attenuate as the fixed-effect structure becomes more saturated. This pattern is especially pronounced for the manual and soft skill indicators: adding 5-digit occupation-by-month fixed effects substantially reduces the estimated coefficients and renders them statistically insignificant.

Finally, I examine the *skill composition* in Figure 7. While the *skill incidence* analysis captures whether a given skill category is mentioned at all, the *skill composition* outcomes measure the relative importance of each category among all skill mentions within an occupation-region cell. These outcomes therefore indicate whether some skill groups gained weight in the overall skill profile of vacancies after the reform. By construction, the four category shares sum to one within each cell, so the estimated coefficients sum to zero across categories: any gain in the relative weight of one group must come at the expense of the others.

In the first two specifications the estimates point to a compositional shift away from soft skills. The relative importance of soft-skills decreases and the offsetting weight accrues mainly to cognitive skills. The relative importance for digital and manual skills remains mostly unchanged. As before, the estimated effects are strongest in the less saturated specifications and attenuate as the fixed-effect structure becomes more demanding. Once 5-digit occupation-by-month fixed effects are included in specifications (3) and (4), the effects on soft- and cognitive-skill intensity are no longer statistically significant.

Taken together, the results based on the gap exposure measure point to a modest but coherent adjustment in skill demand after the minimum wage increase. More strongly exposed occupation–labor-market-region cells increase their *skill quantity*, concentrated in

Figure 7: Effect of gap exposure on *skill composition*



Notes: The figure reports coefficients on the interaction of the gap exposure measure with the post-October-2022 indicator, from separate regressions by outcome. Outcomes are the average shares that the respective categories have within the vacancy task demand. The gap is measured in percentage points. Specifications differ in their time controls, as indicated in the legend; all include occupation (5d) × labor-market-region fixed effects. Horizontal bars show 95 percent confidence intervals based on standard errors clustered at the labor-market-region level. N = 349,843.

cognitive and manual skills. This reflects a greater intensity of existing demands rather than a broadening of skill profiles, as the *skill diversity* does not change. The same reorientation appears in the *incidence* and *composition* of demand, which shift toward manual and cognitive and away from soft skills. Overall, the minimum wage increase led to a small expansion and intensification of cognitive and manual skill requirements, at the expense of soft skills.

4.2 Robustness

I next assess the robustness of the main results along three dimensions. First, I examine the plausibility of the identifying assumptions by estimating event-study specifications and testing for differential pre-trends. Second, I assess whether the results are driven by changes in the composition of vacancies across cells, rather than by changes in the skill content of otherwise comparable postings. Third, I examine the sensitivity of the findings to alternative levels of aggregation.

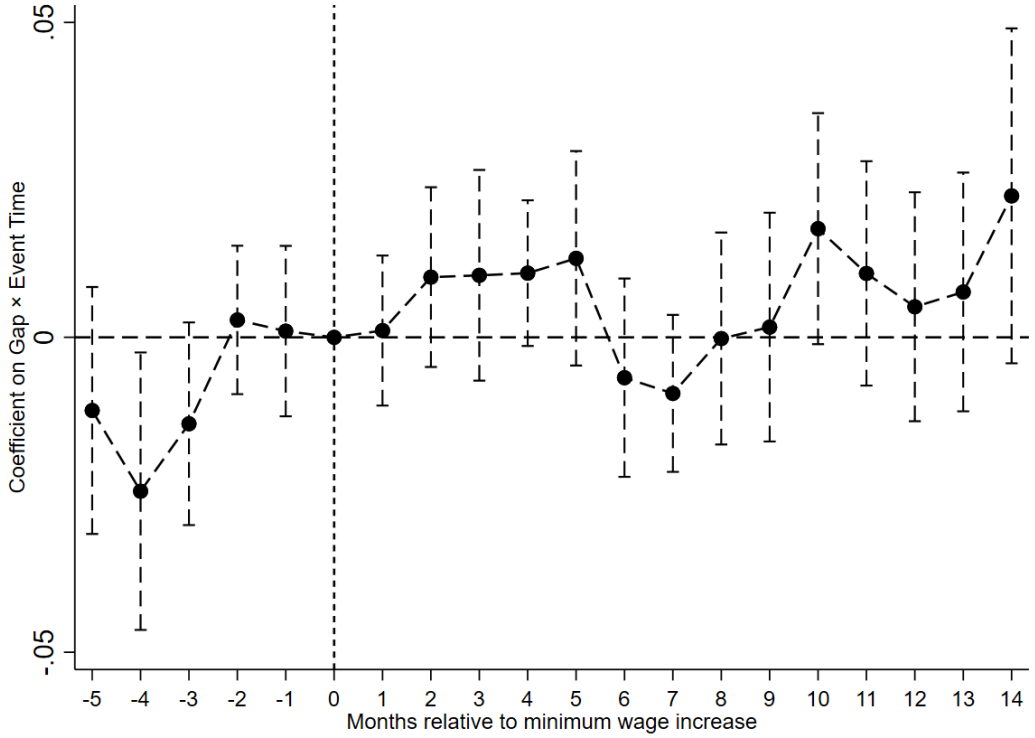
4.2.1 Pre-Trends

A key identifying assumption underlying the difference-in-differences estimates is that, in the absence of the minimum wage increase, skill demand would have evolved similarly across more and less exposed occupation–region cells. While this parallel-trends assumption is inherently untestable for the post-reform period, its plausibility can be assessed by examining whether more exposed cells already followed systematically different trends before the reform. To this end, I estimate the event-study specification outlined in equation (10) for the *skill quantity* and *skill diversity* outcomes.[6] The resulting coefficients for the *skill quantity* are reported in Figure 8.

In the pre-reform period the coefficients are small and mostly insignificant, with a single significant negative estimate five months before the increase. After the reform the coefficients turn positive and are significant at the 10% level in several months. Around six

[6] I focus on the quantity and diversity outcomes because they capture the main margins of adjustment in the baseline analysis. The *skill incidence* outcome is closely related to the quantity outcome, while the *skill composition* outcome is mechanically interdependent across skill categories. I therefore omit them from the event-study discussion.

Figure 8: Event study of gap exposure on the total *skill quantity*



Notes: The figure plots the coefficients β_k from equation (10), interacting the gap exposure measure (in percentage points) with indicators for months relative to the increase. Event time is measured relative to September 2022, the omitted reference period; the increase took effect in October 2022, so $k = 1$ is the first treated month. Fixed effects as in specification (2). Vertical bars show 95 percent confidence intervals based on standard errors clustered at the labor-market-region level. N = 349,843.

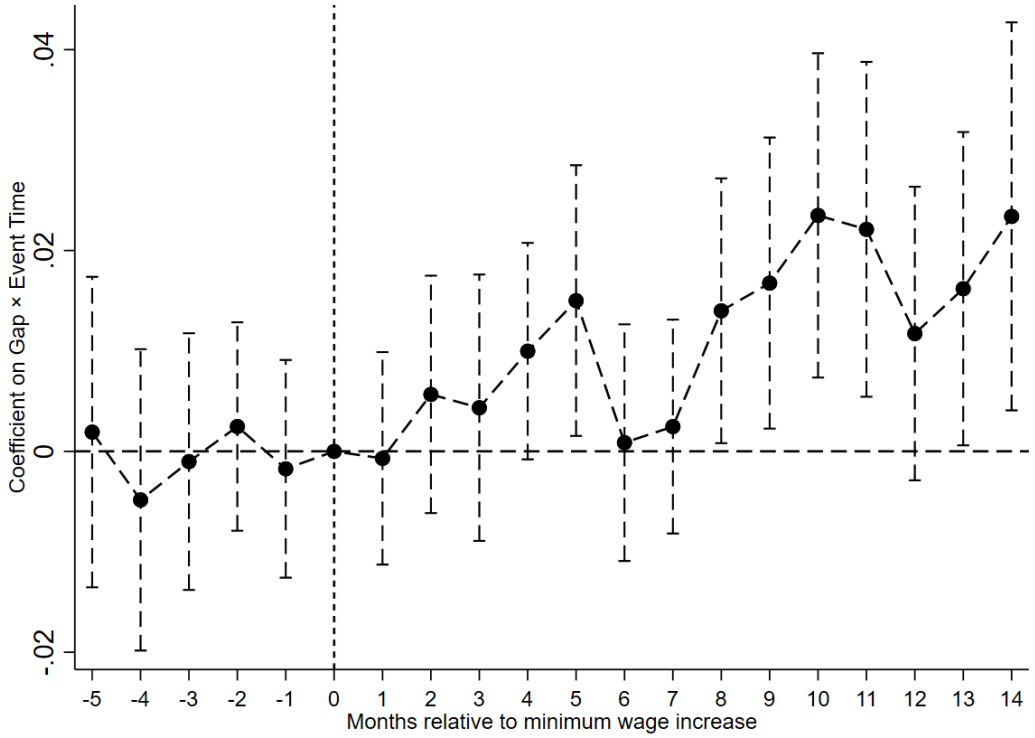
months after the increase they dip and remain at a lower level before rising again toward the end of the period. As in the static analysis, however, the sum of skills is a composite of the four individual skill categories, which warrants examining each separately. The corresponding event-study plots are reported in Appendix Figure A3.

For cognitive skills there is no evidence of differential pre-trends. The post-reform coefficients are largely insignificant in the first months but grow in magnitude and become partly significant later in the period. Digital skills mirror the static estimates: the coefficients are insignificant both before and after the reform, apart from an isolated spike in a single month. Manual skills likewise display no clear pre-trends, followed by an increase in demand after the reform; aside from a three-month dip, this increase is sustained and significant at the 5% level.

Soft skills are the exception. Three of the pre-reform coefficients are clearly negative and significant, and the post-reform period shows a pronounced downward trend. For this category the concern about differential pre-trends is therefore warranted. It does not, however, threaten the main results, since the effect on the number of soft skills was insignificant across all specifications in the static analysis.

The pre-trend in soft skills nonetheless raises the question of whether the weak pre-trend in the total is itself driven by soft skills. To test this, I re-estimate the event study for the total number of skills excluding the soft skill category. The result is shown in Figure 9. Excluding soft skills improves the picture: without them, the event-study estimates exhibit no clear pre-trends and a positive, growing effect after the reform. The aggregate increase in skill demand is thus not an artifact of the soft-skill pre-trend.

Figure 9: Event study of gap exposure on the total *skill quantity* (excluding soft skills)



Notes: The figure plots the coefficients β_k from equation (10), interacting the gap exposure measure (in percentage points) with indicators for months relative to the increase. Event time is measured relative to September 2022, the omitted reference period; the increase took effect in October 2022, so $k = 1$ is the first treated month. Fixed effects as in specification (2). Vertical bars show 95 percent confidence intervals based on standard errors clustered at the labor-market-region level. N = 349,843.

To complement the visual inspection, I conduct joint F-tests of the pre-reform and post-reform coefficients for each outcome; the results are reported in Table 2. The null hypothesis that the pre-reform coefficients are jointly zero cannot be rejected for any outcome except soft skills, consistent with the graphical evidence. The null that the post-reform coefficients are jointly zero is rejected at at least the 5% level for all outcomes except digital skills. The F-tests thus support the visual impression of no systematic differential pre-trends between more and less exposed cells, with the exception of soft skills.

Table 2: Joint significance tests of pre- and post-reform event-study coefficients

	Pre-reform		Post-reform	
Outcome	F	p	F	p
Total skills	1.786	0.120	2.060	0.018
Cognitive skills	0.238	0.945	1.972	0.025
Digital skills	0.225	0.951	1.103	0.361
Manual skills	0.585	0.711	3.281	<0.001
Soft skills	5.331	<0.001	3.617	<0.001
Total excl. soft	0.281	0.923	2.459	0.004

Notes: The table reports F-tests of the joint hypothesis that the event-study coefficients are zero, separately for the pre- and post-reform periods, for the average number of skill mentions per vacancy. Pre-reform tests have 5 and post-reform tests 14 numerator degrees of freedom, with 131 denominator degrees of freedom throughout. September 2022 is the omitted reference period. Fixed effects as in specification (2). Standard errors are clustered at the labor-market-region level. N = 349,843.

Finally, Appendix Figure A4 reports all event-study plots for the more saturated specification (4). Because most coefficients in that specification are already insignificant in the static analysis, the event-study coefficients are likewise mostly indistinguishable from zero in both the pre- and post-reform periods. This specification therefore does not challenge the parallel-trends assumption either.

The event studies for *skill diversity* are also reported in Appendix Figure A5. As these outcomes were already insignificant in the static analysis, the event-study coefficients are similarly insignificant in both periods. The pre-reform coefficients are mostly indistinguishable from zero, with the exception of one or two months for most outcomes, and the post-reform coefficients remain insignificant while drifting mildly downward, echoing the negative but insignificant pattern seen for the static outcomes. Re-estimating under spec-

ification (4) (Appendix Figure A6) pushes the coefficients closer to zero still, reinforcing the impression of no meaningful dynamics.

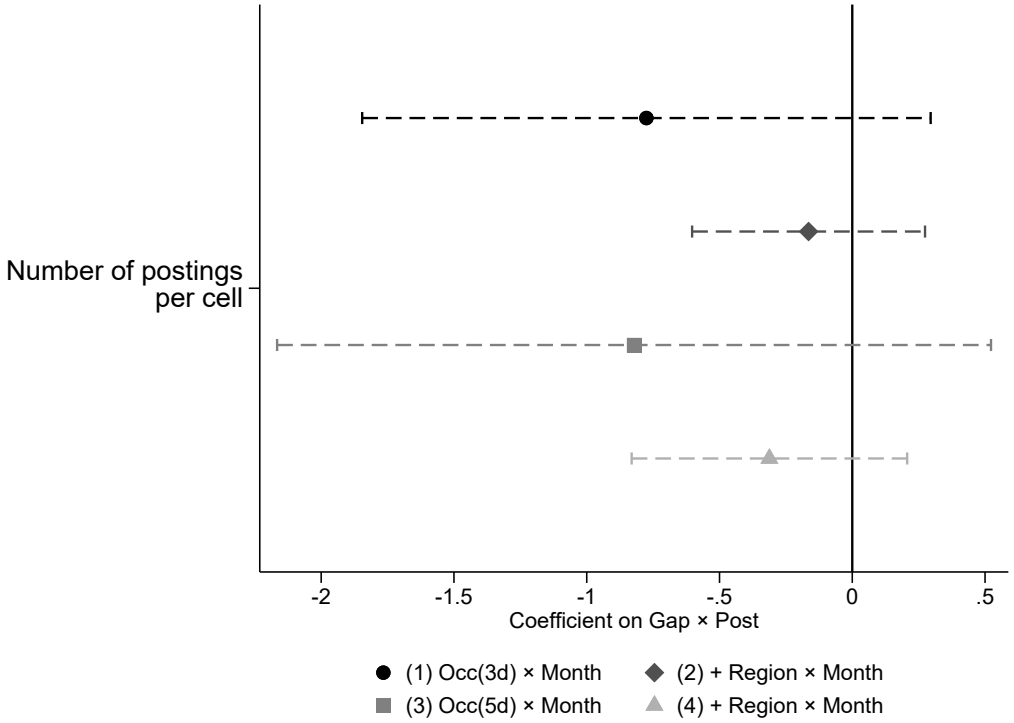
Taken together, the event studies support the parallel-trends assumption underlying the main estimates. With the exception of soft skills, none of the outcomes shows systematic differential trends between more and less exposed cells before the reform, and once soft skills are excluded from the aggregate, the total number of skills is free of pre-trends as well. The post-reform coefficients, where significant, build gradually rather than jumping at the reform date, consistent with a progressive adjustment of skill demand.

4.2.2 Composition

A further concern for the validity of the main results is that the minimum wage increase may have changed the composition of online job postings. If more exposed occupations were posted less often, or if the mix of advertised occupations changed, the estimated effects on skill demand could reflect these compositional shifts rather than a genuine change in the task demand of firms. To rule this out, I re-estimate equation (9) using compositional attributes of the postings as outcomes.

I first use the number of postings per occupation–region cell as the outcome. Because the skill measures are averages over the postings in a cell, a change in how many vacancies firms posted could shift the composition of that average and move the outcome mechanically. In a regression on the number of postings, the interaction between the post indicator and the exposure measure captures any differential effect the minimum wage had on posting behavior across more and less exposed cells. The estimates are reported in Figure 10. Across all fixed-effect specifications the coefficient on the interaction is negative but statistically insignificant, and the confidence intervals are wide. Exposure thus did not measurably affect the number of postings per cell. This is consistent with Dorau et al. (2025), who likewise find no notable decline in vacancy volumes following the increase.

Figure 10: Effect of gap exposure on the number of postings per cell



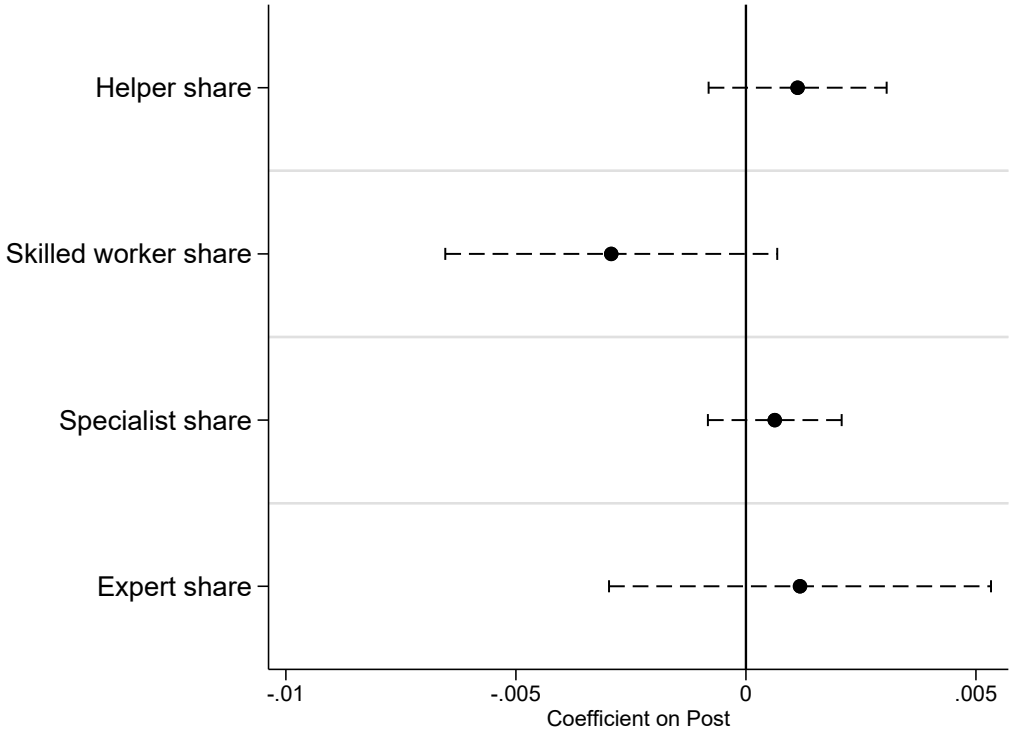
Notes: The figure reports coefficients on the interaction of the gap exposure measure (in percentage points) with the post-October-2022 indicator. The outcome is the number of vacancies posted in an occupation–labor-market-region cell in a given month. Specifications differ in their time controls, as indicated in the legend; all include occupation-by-labor-market-region fixed effects. Horizontal bars show 95 percent confidence intervals based on standard errors clustered at the labor-market-region level. N = 349,843.

A second potential channel is that firms facing higher labor costs shift their hiring toward higher-qualified workers. To assess this, I use the requirement-level composition of postings as the outcome. Aggregating to the 3-digit occupation level, I compute the share of postings in each cell falling into each of the four requirement levels — helper, skilled worker, specialist, and expert — and regress these shares on the post-reform indicator, including occupation-by-region fixed effects. Unlike the other specifications, this regression does not interact the post indicator with exposure. The reason is mechanical: the gap is constructed from the wage distribution, and cells with a larger share of helper and skilled-worker postings necessarily exhibit higher exposure. Regressing the gap on a requirement-level share would therefore build this correlation into the regression by construction. The within-cell post indicator instead captures the aggregate shift in the requirement mix over the reform period. Because the specification includes only a post indicator, it cannot accommodate time fixed effects, which would absorb the treatment variable entirely. The regression therefore includes occupation-by-region fixed effects alone.

The estimates are shown in Figure 11. None of the four requirement-level shares exhibits a significant post-reform change. The composition of advertised requirement levels therefore remained stable across the reform period, providing no indication that the skill-demand results are an artifact of a changing mix of advertised job levels. This is also consistent with the findings of Dorau et al. (2025), who likewise report no significant changes in the requirement levels of advertised positions in response to the 2022 minimum wage increase.

Together, these checks indicate that the minimum wage increase did not induce fundamental changes in the volume or composition of labor demand in more exposed cells. The estimated effects on skill demand can thus be interpreted as genuine adjustments in the content of vacancies, rather than a by-product of a changing composition of postings.

Figure 11: Effect of minimum wage increase on the requirement-level composition of postings



Notes: The figure reports coefficients of a post-October-2022 indicator. Outcomes are the shares of postings in a 3-digit occupation–labor-market-region cell falling into each of the four KldB requirement levels. Because the requirement level defines the outcome, exposure is measured at the 3-digit occupation level. Only Kldb 3-digit × labor-market-region fixed effects are included. Horizontal bars show 95 percent confidence intervals based on standard errors clustered at the labor-market-region level. N = 219,918.

4.2.3 Aggregation

To ensure that the results are not driven by a particular measurement or aggregation choice, I probe their robustness along four dimensions: the exposure measure, the regional aggregation, the functional form of exposure, and the level of aggregation itself.

First, I examine whether the results depend on how minimum-wage exposure is measured, repeating the full set of analyses with the bite measure in place of the gap. The estimates are reported in Appendix Figure A7. Because the two measures differ in scale, the magnitudes are not directly comparable, but qualitatively the findings are unchanged: exposure raises the *skill quantity*, driven by cognitive and manual skills, while the *skill diversity* remains mostly flat. The corresponding event studies likewise resemble those for the gap and show no evidence of differential pre-trends (see Appendix Figure A8).[7]

Second, I assess sensitivity to the regional aggregation. I re-estimate the main specifications aggregating to the federal-state level, which allows me to apply the representative weights of the Earnings Survey when constructing the gap. The change carries through the entire estimation: cells are now defined by occupation and federal state rather than labor market region, and the fixed effects and clustered standard errors are adjusted accordingly. The estimates, reported in Appendix Figure A9, again leave the qualitative conclusions intact.

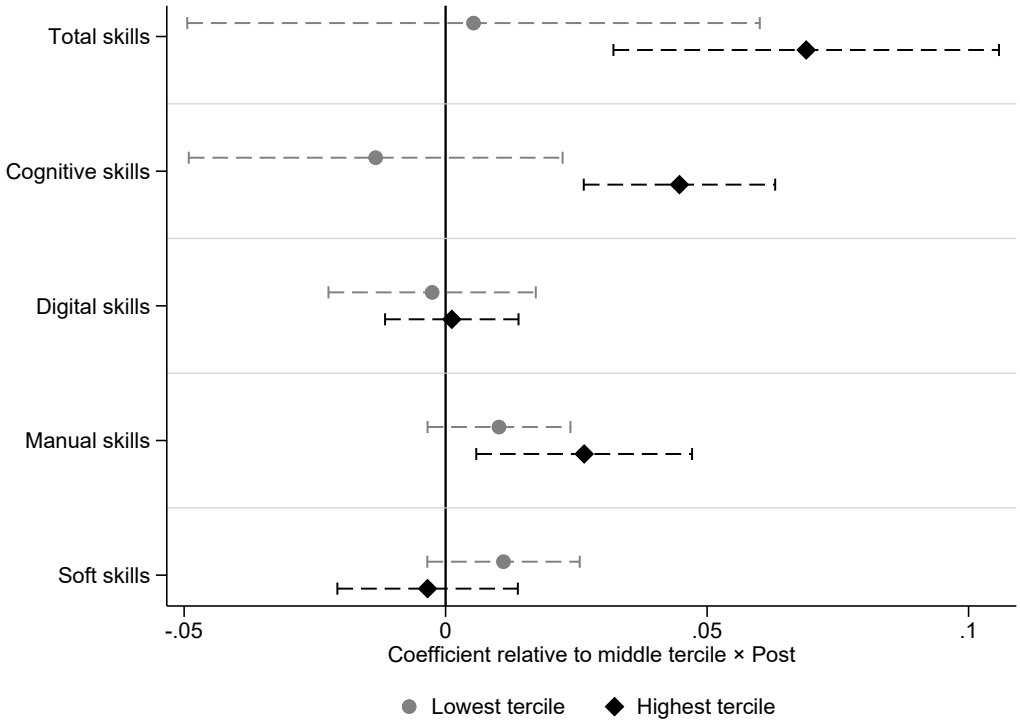
Third, I address the concern that the continuous specification may mask where the effect originates, and in particular whether lightly exposed cells contribute to it. I divide the sample into terciles of the gap distribution and replace the single continuous interaction in equation (9) with two interactions: one for the bottom tercile and one for the top tercile, with the middle tercile as the reference group. This allows the most and least exposed cells to be distinguished directly.[8] Figure 12 reports the results for *skill quantity*; the remaining outcomes are shown in Appendix Figures A10–A12. For the number of skills the effect is concentrated entirely in the most exposed cells. Relative to the middle tercile, the bottom tercile — cells with essentially no exposure — shows no effect on skill

[7] Soft skills seem to be once more an outlier with some hints of pre-reform trends. Removing them from the aggregate sum improves the overall trends of the sum of skills outcome.

[8] The bottom tercile of the gap distribution has a median exposure of zero, so this group effectively consists of unexposed cells.

demand, while all significant effects come from the top tercile. The same pattern holds for the *skill incidence* and *skill composition* outcomes in the Appendix. The *skill diversity* outcome in Figure A10 is instructive: cells with low exposure broaden their skill demand, requesting a wider range of distinct skills, whereas the most exposed cells show no such broadening. The concentration of skill demand documented above is thus specific to the cells where the minimum wage bound most tightly.

Figure 12: Effect of gap exposure on *skill quantity* by exposure tercile

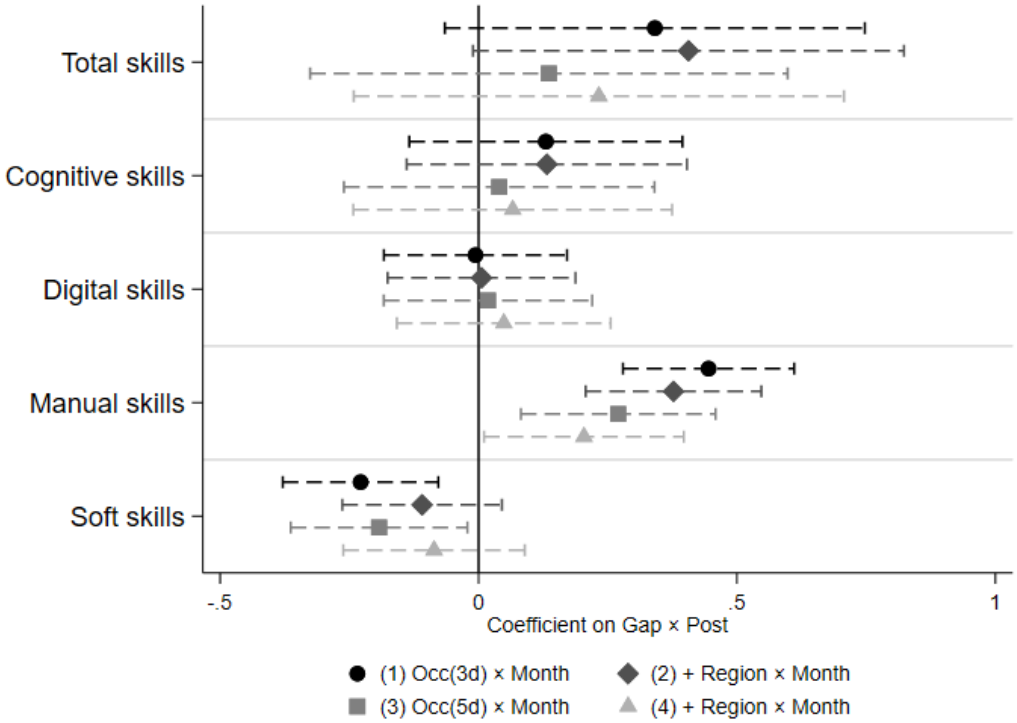


Notes: The figure reports coefficients on the interactions of the post-October-2022 indicator with indicators for the bottom and top terciles of the gap distribution; the middle tercile is the omitted reference group. Each coefficient therefore gives the differential post-reform change in the respective group relative to cells of intermediate exposure. Outcomes are the average number of skill mentions per vacancy in an occupation–labor-market-region cell. Fixed effects as in specification (2). Horizontal bars show 95 percent confidence intervals based on standard errors clustered at the labor-market-region level. N = 349,843.

Finally, all analyses so far aggregate the vacancy data to cells. As a last step, I move to the individual posting level, merging exposure onto the occupation advertised in each posting and estimating the effect on the number of skills the posting requires. Working at the posting level rules out some cell-level outcomes, such as the *skill diversity* or the *skill incidence*. In return, it offers many more observations and lets me include firm

fixed effects, which absorb time-invariant differences in vacancies' skill content across firms. Figure 13 reports the posting-level estimates for the number of skills found in the posting. The results echo the cell-level analysis: the total number of skills rises, significant at the 10% level, driven mostly by manual skills, which are significantly positive across all specifications. Cognitive and digital skills show no significant change. Soft skills decline slightly, but only in the sparser specifications; once region-by-month fixed effects are included, the coefficient becomes insignificant.

Figure 13: Effect of gap exposure on *skill quantity* at the posting level



Notes: The figure reports coefficients on the interaction of the gap exposure measure (in percentage points) with the post-October-2022 indicator, estimated at the level of the individual vacancy rather than the occupation–region cell. Outcomes are the number of skill mentions in a posting. Exposure is merged onto the occupation advertised in the posting. Specifications differ in their controls, as indicated in the legend; all include firm fixed effects and occupation (5d) × labor-market-region fixed effects. Horizontal bars show 95 percent confidence intervals based on standard errors clustered at the labor-market-region level. N = 5,856,919.

Across all robustness checks, the central finding is robust: greater exposure to the minimum wage raises the number of skills firms request, concentrated in manual and cognitive requirements, and the effect originates in the most exposed cells.

5 Mechanisms

The results so far establish that greater exposure to the minimum wage raises the number of skills firms request, concentrated in cognitive and manual requirements, while leaving the *skill diversity* broadly unchanged. This section asks how firms adjust the content of their skill demand. I consider two mechanisms. The first is skill concentration: whether more exposed employers focus their demand on the skills most central to an occupation rather than its more peripheral ones. The second is skill upgrading: whether the required skills become *better*, which would be an improvement of the jobs.

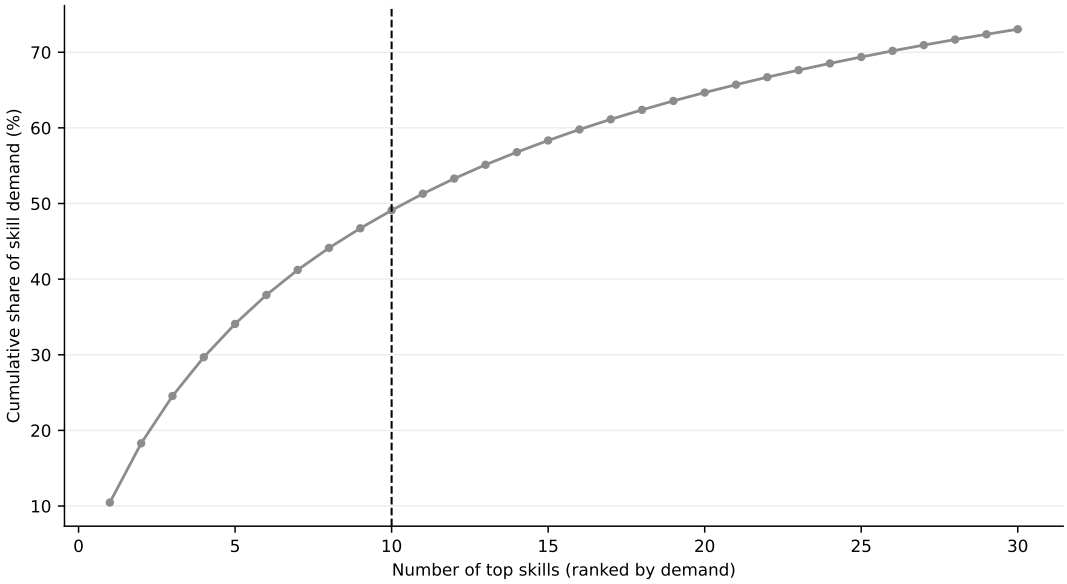
5.1 Skill Concentration

The results so far show that firms increase their skill demand without broadening it. This suggests that the increase stems primarily from existing skills being demanded more intensively, rather than from firms adding new skills. To test this directly, I introduce a distinction between *core* and *satellite* skills.

Core skills are those central to an occupation: the requirements that appear in most vacancies for that job and correspond to its principal tasks. Satellite skills are more peripheral, appearing only infrequently in postings for the occupation. This distinction is important because skill demand within occupations is highly concentrated. Figure 14 plots, averaged across occupations, the cumulative share of an occupation's total skill mentions accounted for by its most frequently demanded skills. The single most requested skill alone accounts for around 10 percent of all keyword hits for that occupation, the top five for roughly 34 percent, and the top ten for about half of all keywords. The curve flattens markedly thereafter, with the top thirty skills covering some 73 percent, so that the long tail of remaining requirements contributes little individually. Although occupations may include a large number of distinct skills, only a small set of skills appears repeatedly across vacancies and accounts for most mentions.

To classify skills into the two groups, I exploit the full history of the vacancy data prior to the estimation window, using all postings from January 2017 through March 2022.

Figure 14: Concentration of skill demand within occupations



Notes: The figure plots the cumulative share of an occupation's total skill mentions accounted for by its most frequently demanded skills, ranked in decreasing order and averaged across occupations. The dashed line marks the top-ten cutoff used as the baseline definition of core skills. Skills are counted over all postings in the estimation sample.

Defining the core skills outside the estimation period ensures that the classification is not itself affected by the reform. For each occupation, I pool all postings in this window and record every skill mentioned together with the number of times it is requested, which yields a vector of skill counts summarizing the requirements that characterize the occupation. Ranking the entries of this vector gives its most frequently demanded skills, and I define the top five, ten, and twenty as alternative core sets, with the top ten serving as the baseline.

A fixed cutoff, however, treats all occupations alike, even though the concentration of demand varies across them: ten skills may exhaust the requirements of one occupation while covering only a small fraction of another's. I therefore define an additional, occupation-specific core set consisting of the most frequently demanded skills that jointly account for at least 50 percent of an occupation's total mentions.[9] This holds the coverage of the core fixed rather than its size, and serves as a robustness check on the fixed-cutoff definitions.

The core skill sets defined over the period from 2017 to March 2022 serve as fixed

[9]In practice this entails a list with on average 18 skills.

reference categories for the estimation period. For each posting in the estimation sample, I classify every detected skill according to whether it belongs to the relevant occupation-specific core set under the respective definition. This yields vacancy-level counts of core and satellite skills, from which I am able to calculate the respective shares. Aggregating these measures to the occupation–region–month level gives the average number of core skills per vacancy, the average number of satellite skills per vacancy, and the average core share, which I use as additional outcomes in the estimation framework of Section 3.

Since the core sets are fixed and defined before the estimation window begins, changes in these outcomes cannot arise from a changing definition of what constitutes a core skill. Instead, they capture whether firms shift the relative weight of established versus more peripheral skill requirements in response to the minimum wage increase.

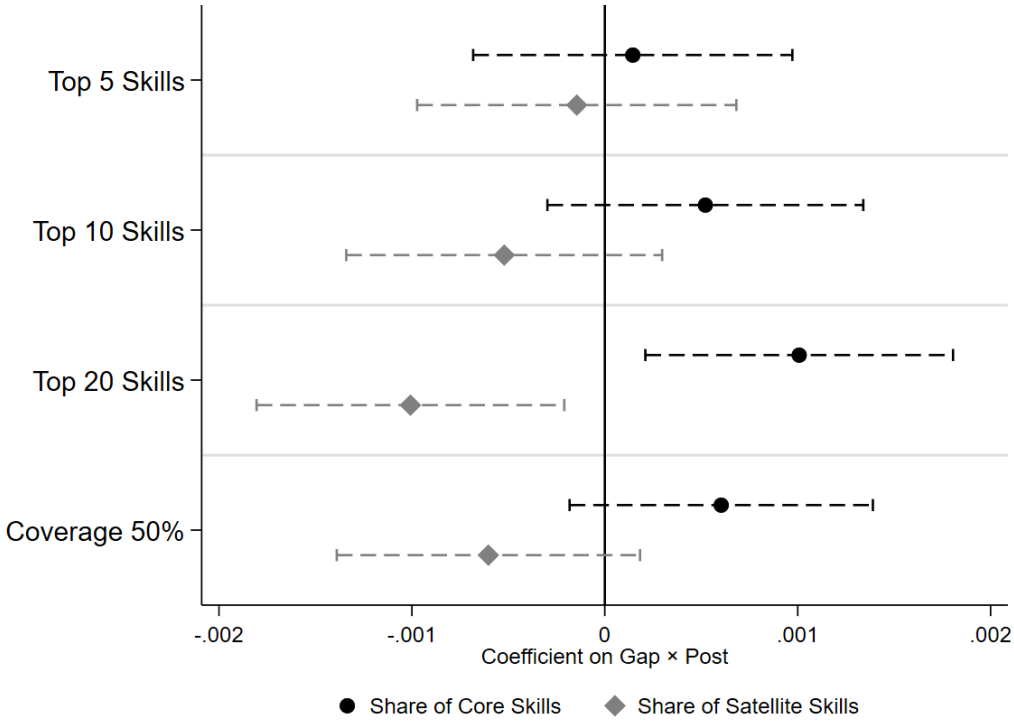
Figure 15 reports the difference-in-differences estimates for the share of core and satellite skills. It uses fixed-effect specification (2) and plots the coefficient on the interaction of exposure and the post indicator for each outcome, with rows distinguishing the alternative core definitions. Because the core and satellite shares sum to one within a posting, the two coefficients are exact mirror images.

Across all definitions, the core share rises in more exposed cells after the reform while the satellite share falls. The effects are not statistically significant when the core is defined narrowly, as the top five or top ten skills, but grow as the core set is widened to include more skills. Under the top-twenty definition, the increase in the core share and the corresponding decline in the satellite share are both significant. The coverage-based definition, which selects on average around eighteen skills per occupation, points the same way, with effects significant at the 10% level.

Under the more saturated specification (4), see Appendix Figure A13, the estimates fall considerably in magnitude but retain their sign and significance, and the pattern across definitions remains visible.

A potential concern with this approach is that skills emerging only during the estimation period cannot be captured by a core set defined over the pre-reform window. Because any skill absent from the pre-defined core is counted as satellite, such newly

Figure 15: Effect of gap exposure on the share of core and satellite skills



Notes: The figure reports coefficients on the interaction of the gap exposure measure (in percentage points) with the post-October-2022 indicator, under specification (2). Outcomes are the core and satellite shares of a vacancy's skill mentions; since the two sum to one, their coefficients mirror each other. Rows correspond to alternative core definitions, fixed over the 2017–March 2022 window. Horizontal bars show 95 percent confidence intervals, clustered at the labor-market-region level. N = 349,843.

emerging skills are automatically classified as satellite, which could bias the core–satellite distinction. This works against the concentration result: if more exposed cells disproportionately adopted new skills, the mechanical effect would raise their satellite share and understate the rise in the core share I document. Empirically, however, the issue is minor. Skills that appear only after the definition window account for a median of just 3.5 percent of all keyword hits in the estimation period, so the requirements omitted by fixing the core ex ante make up a negligible share of observed skill demand. Any bias from omitting these new skills thus runs against the concentration result, so the rising core share, if anything, is estimated conservatively.

Taken together, these results support the interpretation suggested by the main estimates. The increase in the *skill quantity*, unaccompanied by any increase of *skill diversity*, reflects a reallocation of demand toward the requirements most central to an occupation. More exposed firms concentrate their postings on the skills the job genuinely requires and place less weight on peripheral ones.

5.2 Skill Upgrading

A second mechanism through which exposed firms may adjust to higher labor costs is skill upgrading: faced with a higher wage floor, they may raise the complexity of the tasks they advertise, seeking workers whose skills justify the higher pay. A related form of upgrading is documented by Dustmann et al. (2022) for the 2015 introduction of the German minimum wage, who find that the policy reallocated low-wage workers toward larger, higher-paying, and more productive establishments, so that part of the observed wage gain reflects workers moving to better employers rather than higher pay within the same job. Here, I ask whether an analogous upgrading occurs within the vacancy itself: whether more exposed employers begin to ask for the skills characteristic of more demanding jobs.

To operationalize this, I exploit the requirement hierarchy embedded in the occupational classification. The same occupation can be advertised at four requirement levels,

indicated by the fifth digit of the KldB: helper, skilled worker, specialist, and expert.[10] Because higher levels typically presuppose more formal qualification, carry more responsibility, and pay higher wages, I treat the higher-level variants of an occupation as the more demanding ones, the *targets*. If the minimum wage pushes low-level postings toward the requirements of higher-level jobs, the skill profiles of the two levels should converge.

I measure this convergence with cosine similarity between the skill profiles of different requirement levels within the same occupation. As in the core–satellite analysis, I use the pre-estimation window to fix the frame of reference: for each 3-digit occupation I collect the set of skills demanded anywhere across its requirement levels before April 2022, and this set defines the vocabulary — the axes along which profiles are compared. Fixing the vocabulary ex ante ensures that any measured convergence reflects movement in the profiles themselves rather than a shifting set of skills over which they are compared.

Within the estimation window, I then construct for each labor market region, occupation, requirement level, and month a skill prevalence vector, whose entries give the share of postings in that cell mentioning each skill. Cosine similarity between the vectors of two requirement levels in the same region–occupation–month then measures how alike their skill profiles are, with higher values indicating greater overlap. I compute this for each pairing of a lower and a higher level, and additionally for a pooled high target combining specialists and experts. Similarity is defined only where both sides are observed with at least three postings in the cell-month, mirroring the minimum cell size applied to the exposure measure. Each similarity is attached to the requirement level of the lower, potentially upgrading side, so that specialist and expert levels enter only as the higher level of a comparison, never as an upgrading one.

Since convergence between two moving profiles is silent about which side moved, I complement these measures with a directional one. For each level I compute the cosine similarity between its monthly profile and its own national pre-reform profile. A decline in this self-similarity for low levels, unaccompanied by a comparable decline at higher levels, would indicate that the convergence is driven by low-level postings moving toward

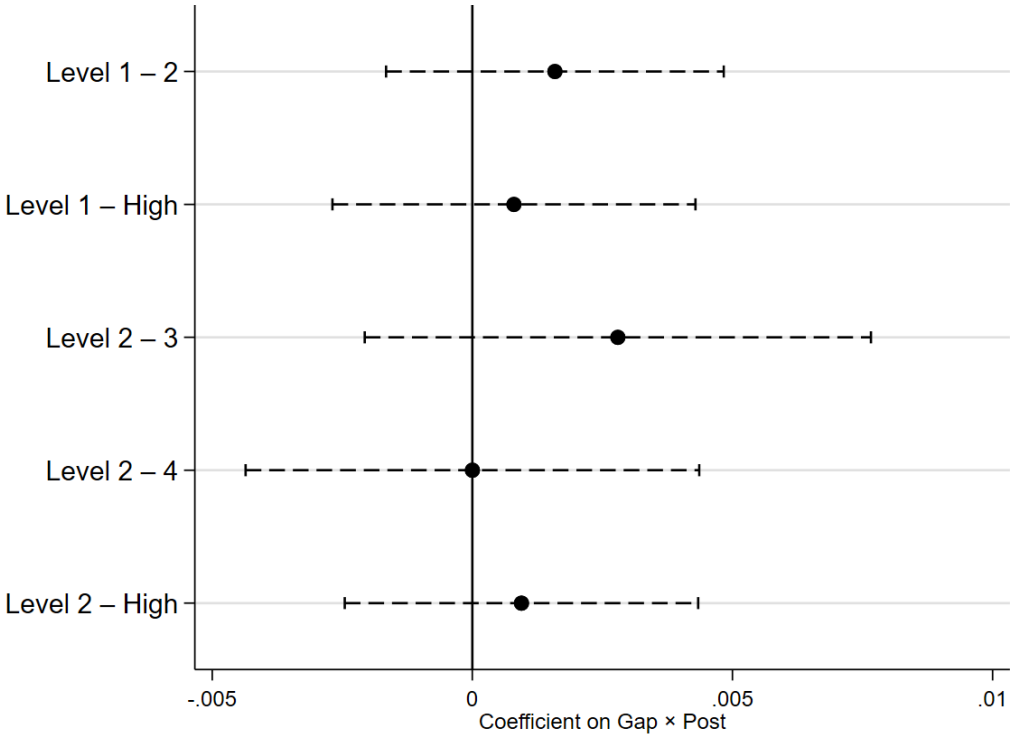
[10] Throughout this analysis I refer to the requirement levels numerically: helper jobs are level 1, skilled worker jobs level 2, specialist jobs level 3, and expert jobs level 4.

high-level requirements rather than the reverse.

These similarity measures then enter the estimation framework of Section 3 as outcomes, so that I can test whether the skill profiles of low- and high-requirement jobs converged more strongly in cells more exposed to the minimum wage.

Figure 16 reports the estimates for the between-level similarities. None of the level pairings shows a significant change in similarity following the reform. The point estimates are uniformly small and the confidence intervals are large. Thus, there is no evidence that the skill profiles of helper and skilled-worker postings converged toward those of more demanding requirement levels in more exposed cells — neither toward the next rung of the hierarchy nor toward the pooled specialist and expert profiles.

Figure 16: Effect of gap exposure on skill-profile similarity across requirement levels

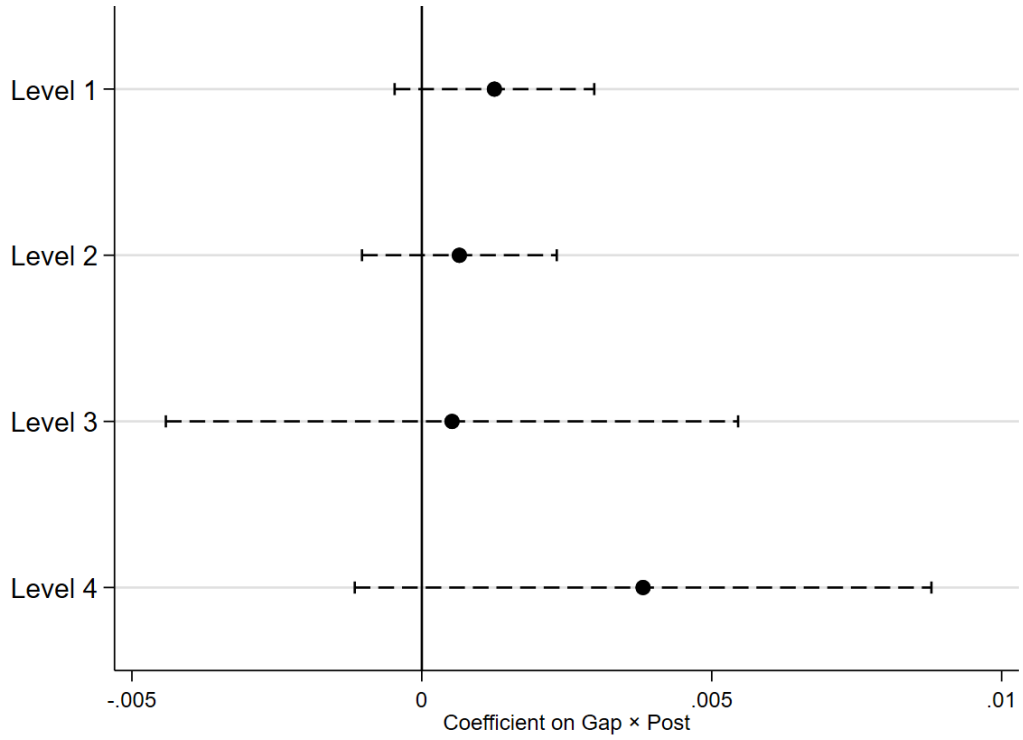


Notes: The figure reports coefficients on the interaction of the gap exposure measure (in percentage points) with the post-October-2022 indicator, under specification (2). The outcome is the cosine similarity between the skill profiles of two requirement levels within the same occupation–labor-market-region cell in a given month, computed over a fixed skill vocabulary defined in the 2017–March 2022 window; higher values indicate more similar profiles. Rows correspond to level pairings, where "High" pools specialists and experts. Horizontal bars show 95 percent confidence intervals, clustered at the labor-market-region level. N differs by row and ranges from 11,162 to 47,336.

The directional measures in Figure 17 point the same way. Here the outcome is the

similarity of each level's monthly profile to its own national pre-reform profile, so that a decline would indicate a level moving away from its established skill mix. No level shows such a decline; if anything, the coefficients are weakly positive, implying that profiles remained close to their pre-reform shape. The largest point estimate appears for expert jobs, but it is imprecisely estimated and, given that expert occupations are essentially unexposed to the minimum wage, an economically implausible margin of adjustment.

Figure 17: Effect of gap exposure on skill-profile stability by requirement level



Notes: The figure reports coefficients on the interaction of the gap exposure measure (in percentage points) with the post-October-2022 indicator, under specification (2). The outcome is the cosine similarity between a requirement level's monthly skill profile and its own national pre-reform profile; lower values indicate a larger departure from the pre-reform skill mix. Rows correspond to requirement levels 1 (helper) through 4 (expert). Horizontal bars show 95 percent confidence intervals, clustered at the labor-market-region level. N differs by row and ranges from 29,394 to 98,453.

The similarity measures compare the entire skill profile of two requirement levels, and across the full vector no convergence is detectable. This is a demanding test. Each skill profile contains a large number of skills, many of which appear only rarely. If upgrading occurs mainly through a small set of skills that distinguishes higher-level jobs, this may be difficult to detect in a comparison of the full profiles. Therefore, I turn to a second, more targeted measure that focuses on the skills most characteristic of each requirement

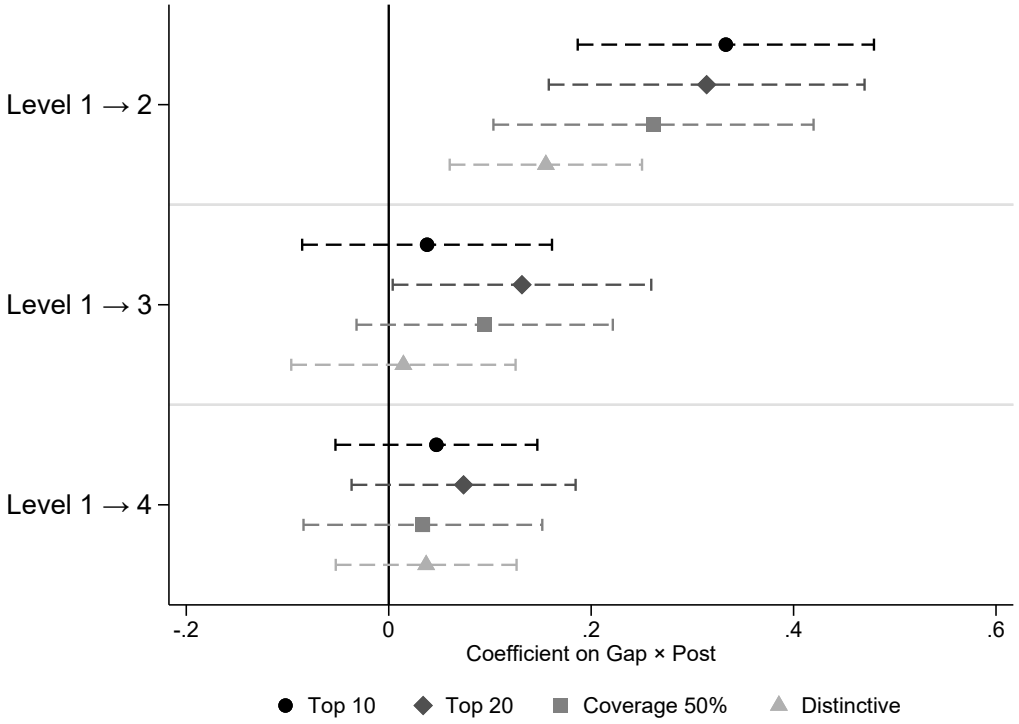
level, adapting the logic of the core–satellite distinction from Section 5.1.

Using the same pre-estimation definition window, I identify for each occupation and requirement level the skills typical of that level, applying the same alternative definitions as before: the top ten and top twenty skills by frequency, and the smallest set covering half of all mentions. For a posting at a given level, I then compute the share of its skill mentions that fall within the typical set of each higher level, and average these shares across postings within an occupation–region–month cell. The resulting share is the outcome. It reflects how far the skills requested in low-level postings overlap with those of higher-level jobs. Because helper and skilled-worker postings are the only ones that can upgrade, specialist and expert levels enter solely as targets.

A concern with this measure is that some skills are demanded ubiquitously across the hierarchy — teamwork or familiarity with standard office software, for instance — so that a low-level posting may appear to draw on higher-level requirements merely by mentioning generic skills. To address this, I construct a fourth, more restrictive definition. A skill counts as distinctive of a higher level if it is mentioned in at least five percent of that level's postings and is at least five percentage points more prevalent there than at the upgrader's own level. This removes requirements common to both levels and retains only those that genuinely separate the higher-level job from the lower one.

Figure 18 reports the estimates for helper postings. In contrast to the similarity results, there is clear evidence of upgrading toward the adjacent level: more exposed cells show a significant increase in the share of helper postings' skill mentions that belong to the skilled-worker skill set. The effect is significant under all four definitions, including the distinctive one, which indicates that it is not an artifact of generic skills shared across levels. The magnitudes decline as the definition tightens, from around 0.33 under the top-ten definition to roughly 0.15 for distinctive skills, which is what one would expect, since the distinctive sets are smaller and exclude the ubiquitous requirements that inflate the broader measures. The upgrading does not extend further up the hierarchy: the estimates for the specialist and expert sets are small and, with one borderline exception, statistically insignificant.

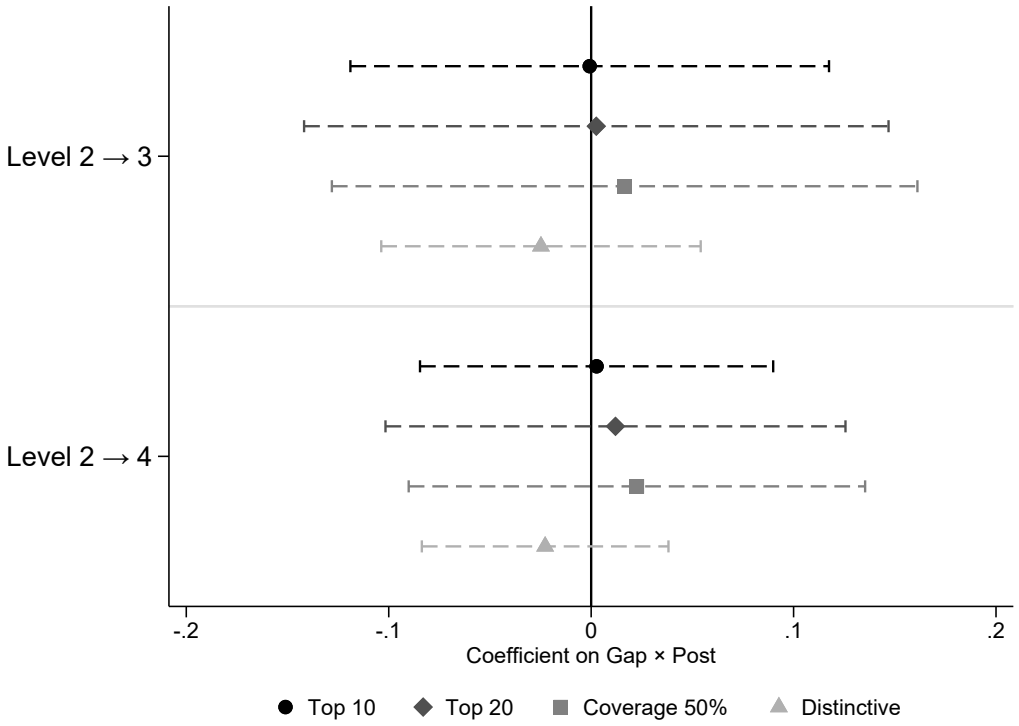
Figure 18: Effect of gap exposure on skill upgrading: helper postings



Notes: The figure reports coefficients on the interaction of the gap exposure measure (in percentage points) with the post-October-2022 indicator, under specification (2). The outcome is the share of a posting's skill mentions that fall within the skills typical of a higher requirement level, averaged over an occupation–labor-market-region cell. Rows correspond to the higher target level; markers distinguish alternative definitions of typical skills (legend), where the distinctive set excludes skills common to both levels. Typical-skill sets are fixed over the 2017–March 2022 window. Horizontal bars show 95 percent confidence intervals, clustered at the labor-market-region level. N = 43,609.

Figure 19 reports the corresponding estimates for skilled-worker postings, which can upgrade only toward specialist and expert requirements. Here, there is no evidence of upgrading at all: the point estimates are essentially zero under every definition and target level, with confidence intervals that comfortably span zero.

Figure 19: Effect of gap exposure on skill upgrading: skilled worker postings



Notes: The figure reports coefficients on the interaction of the gap exposure measure (in percentage points) with the post-October-2022 indicator, under specification (2). The outcome is the share of a posting's skill mentions that fall within the skills typical of a higher requirement level, averaged over an occupation–labor-market-region cell. Rows correspond to the higher target level; markers distinguish alternative definitions of typical skills (legend), where the distinctive set excludes skills common to both levels. Typical-skill sets are fixed over the 2017–March 2022 window. Horizontal bars show 95 percent confidence intervals, clustered at the labor-market-region level. N = 139,801.

Taken together, the two approaches to upgrading yield a consistent and interpretable pattern. Across the full skill profile, low- and high-requirement postings did not converge. But when attention is restricted to the skills that actually characterize a higher-level job, a shift emerges — confined to helper postings and to the immediately adjacent rung of the hierarchy. More exposed employers advertising helper positions began to ask for more of what skilled-worker jobs typically require, while leaving the bulk of the profile unchanged and without reaching toward specialist or expert requirements. Skill upgrading

in response to the minimum wage is therefore real but narrow: it operates at the bottom of the requirement hierarchy, where the reform binds most tightly, and extends only one step upward.

6 Conclusion

This paper examines whether the 2022 increase in the German statutory minimum wage from €9.82 to €12 affected the task content of labor demand. This margin has received little attention in the minimum-wage literature, which has mostly focused on wages, working hours, employment, and vacancies. To examine it, I combine administrative wage data from the German Earnings Survey with a large data set of online job vacancies provided by Palturai/Finbot. I extract firms' skill requirements from the vacancy texts using a keyword-based dictionary based on BERUFENET and group them into cognitive, digital, manual, and soft skills. Because the reform raised a uniform national wage floor, I identify its effects from differences in pre-reform exposure across occupation–region cells. Exposure is measured by both the bite, capturing the share of affected workers, and the gap, capturing the depth of the wage shortfall, and enters a difference-in-differences design with continuous treatment intensity.

The central finding is that firms did adjust the content of their labor demand, but modestly and along specific margins. More exposed occupation–labor-market cells request more skills per vacancy after the reform, and the increase is concentrated in cognitive and manual requirements, while digital and soft skills are unaffected. This is an adjustment in the intensity of demand for skills already central to the job rather than asking for a wider range as the *skill variety* does not rise. The same reorientation appears for the *skill incidence*, where manual skill requirements spread across a larger share of postings and soft skill requirements recede, and in the *skill composition* of demand, which tilts away from soft skills. The effects are economically small and they attenuate as the fixed-effect structure absorbs more of the identifying variation. They are, however, consistent across exposure measures, robust to alternative regional aggregations and to a posting-

level specification with firm fixed effects, and, importantly, concentrated entirely in the most exposed cells: the tercile analysis shows no response where the reform did not bind. Further robustness checks on the volume and requirement-level composition of postings reveal no compositional shifts, echoing Dorau et al. (2025), so the estimates reflect genuine changes in the content of vacancies rather than a changing mix of advertised jobs.

Two mechanisms clarify how this adjustment operates. First, more exposed employers concentrate their demand on the skills most central to an occupation: using a core–satellite distinction fixed over the pre-reform period, the core share of requested skills rises and the satellite share falls, confirming that the additional skill mentions reflect a reallocation toward established requirements rather than the adoption of new ones. Second, there is evidence of narrow skill upgrading. While the full skill profiles of low- and high-requirement postings do not converge, a more targeted measure focusing on the skills that distinctively characterize a higher-level job shows that exposed employers advertising helper positions began to ask for more of what skilled-worker jobs typically require. This upgrading is limited to the bottom of the requirement hierarchy, where the minimum wage binds hardest, and reaches only one level up. There is no similar shift among skilled-worker postings, and none toward specialist or expert requirements.

Taken together, these results add a task-based margin to the emerging picture of the 2022 reform. Even where the literature finds muted employment effects, firms facing a binding wage floor appear to ask more of prospective hires, requesting skills that are more numerous, more central, and more demanding. This fits theories in which higher labor costs lead firms to reorganize production and raise the task intensity expected of each worker (Lazear 2000, Acemoglu & Autor 2011). The finding that estimated effects vary sharply with the level of spatial and occupational aggregation further underscores that firms' responses are regionally heterogeneous and easily masked in more aggregated data.

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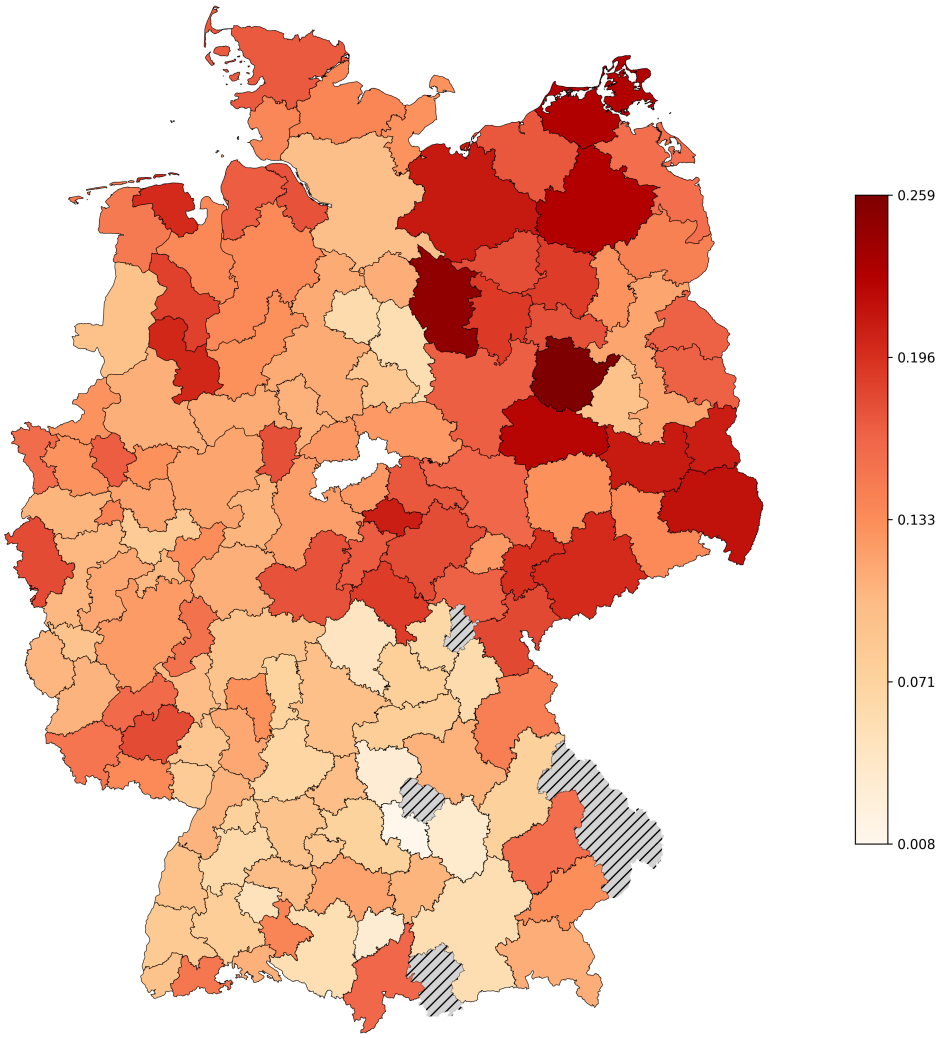
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Appendix

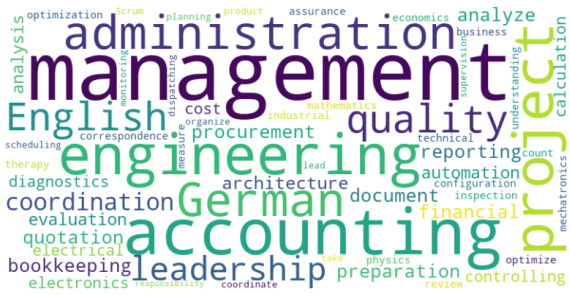
A Figures

Figure A1: Regional Dimension of Bite Exposure



Notes: Average bite exposure per labor-market region in April 2022. Darker colors indicate a higher exposure.
Source: German Earnings Survey, own calculations.

Figure A2: Word clouds for different skill groups



(a) Cognitive Skills



(b) Digital Skills



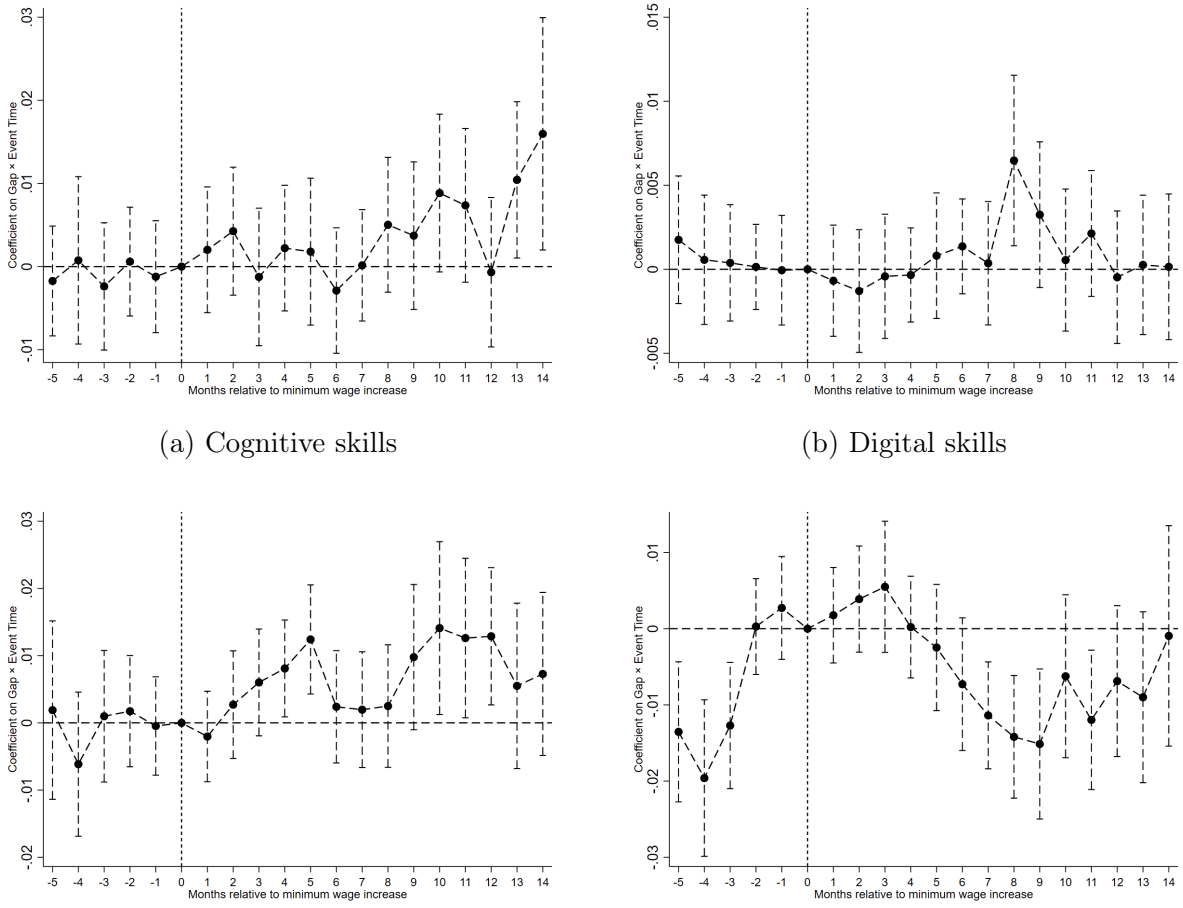
(c) Manual Skills



(d) Soft Skills

Notes: Most common keywords per skill category. Size of the keyword corresponds to the frequency of appearance.
Source: Online job vacancy data, own calculations.

Figure A3: Event studies on the *skill quantity* by skill category



(a) Cognitive skills

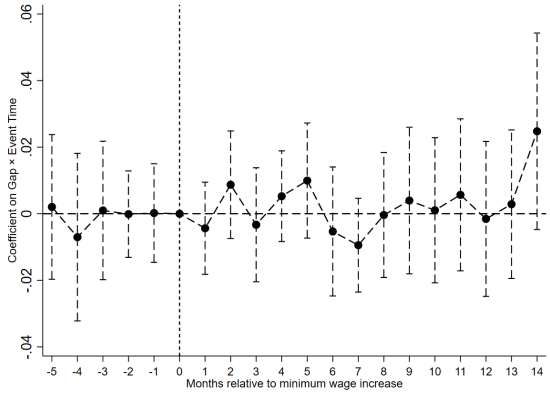
(b) Digital skills

(c) Manual skills

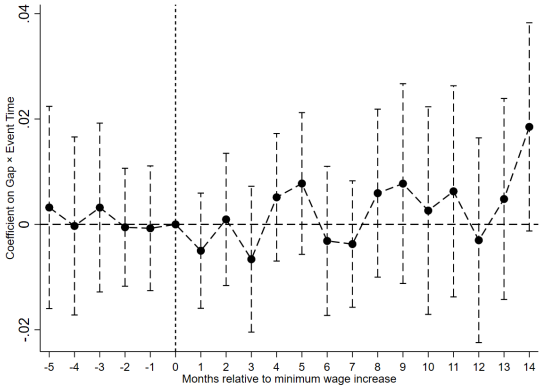
(d) Soft skills

Notes: The figure plots the coefficients β_k from equation (10), interacting the gap exposure measure (in percentage points) with indicators for months relative to the increase. Event time is measured relative to September 2022, the omitted reference period; the increase took effect in October 2022, so $k = 1$ is the first treated month. Fixed effects as in specification (2). Every panel refers to a different outcome variable. Vertical bars show 95 percent confidence intervals based on standard errors clustered at the labor-market-region level. N = 349,843.

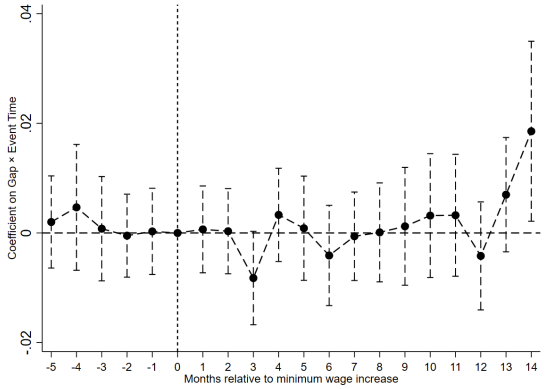
Figure A4: Event studies on the *skill quantity* by skill category (saturated FE specification)



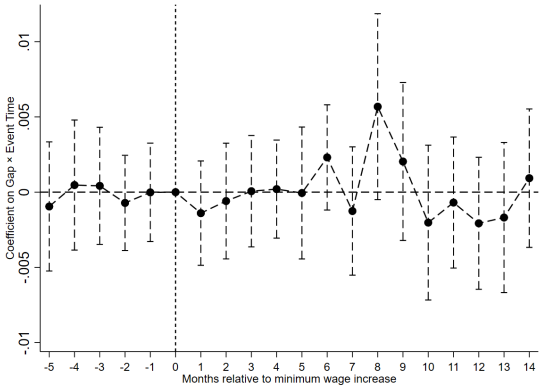
(a) Sum of skills



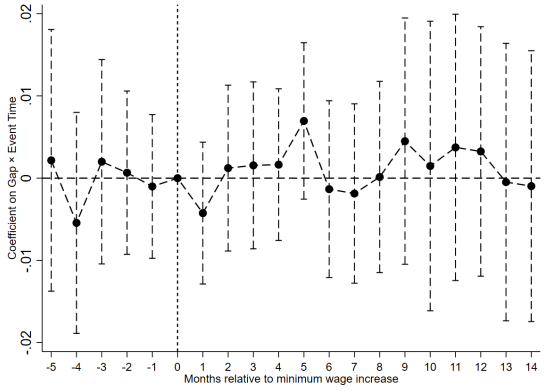
(b) Sum of skills (without soft)



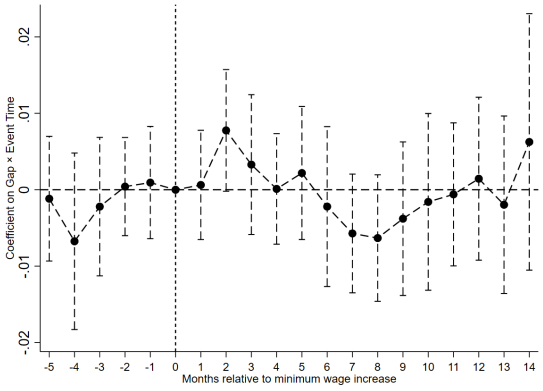
(c) Cognitive skills



(d) Digital skills



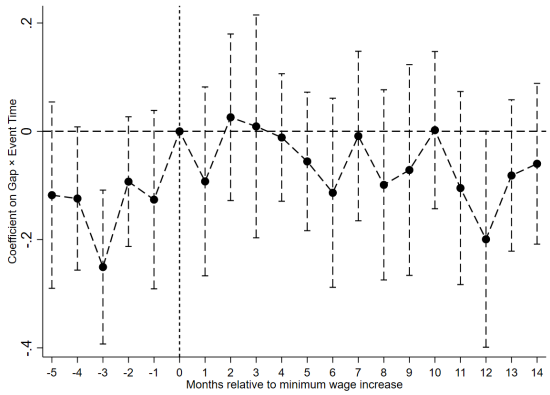
(e) Manual skills



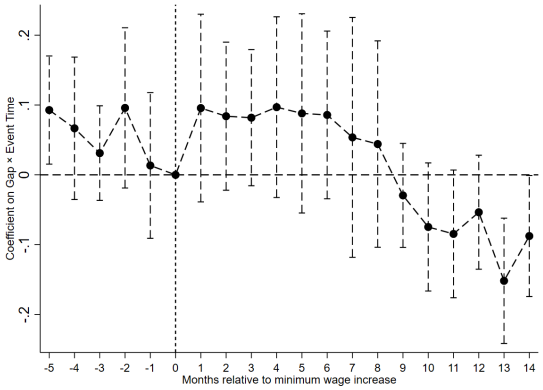
(f) Soft skills

Notes: The figure plots the coefficients β_k from equation (10), interacting the gap exposure measure (in percentage points) with indicators for months relative to the increase. Event time is measured relative to September 2022, the omitted reference period; the increase took effect in October 2022, so $k = 1$ is the first treated month. Fixed effects as in specification (4). Every panel refers to a different outcome variable. Vertical bars show 95 percent confidence intervals based on standard errors clustered at the labor-market-region level. N = 349,843.

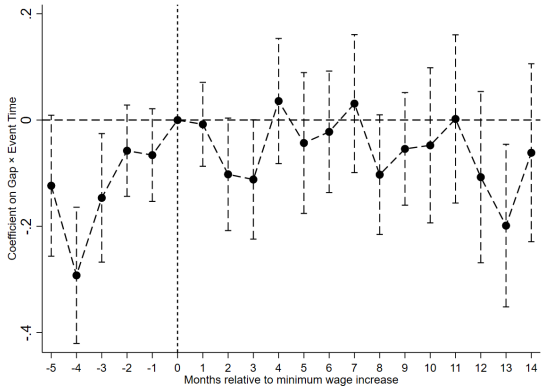
Figure A5: Event studies on the *skill diversity* by skill category



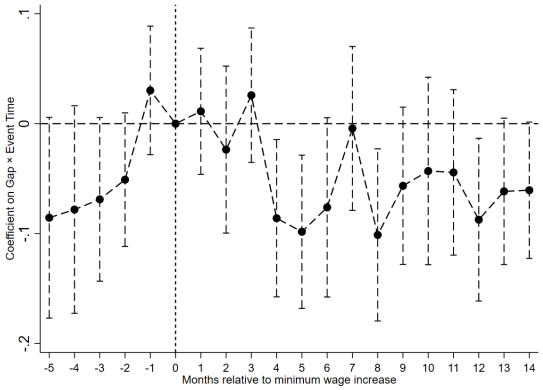
(a) Cognitive skills



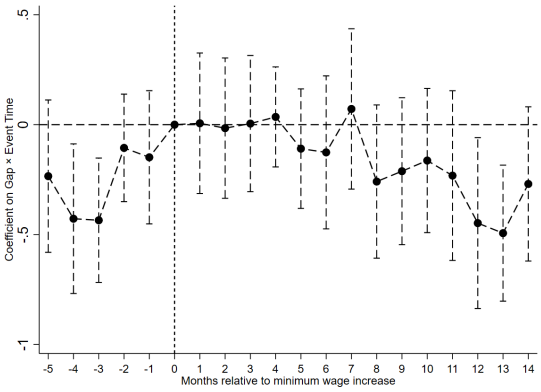
(b) Digital skills



(c) Manual Skills



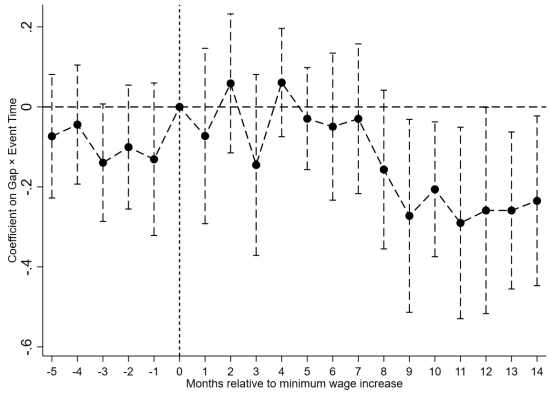
(d) Soft skills



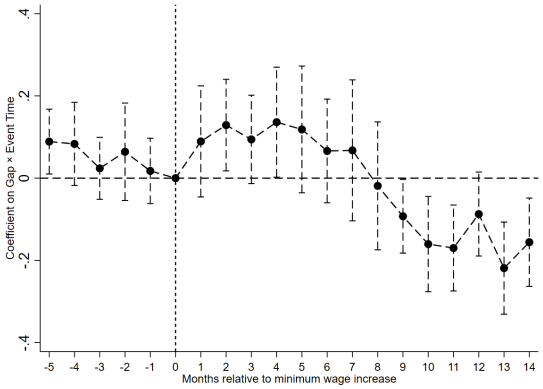
(e) Sum of skills

Notes: The figure plots the coefficients β_k from equation (10), interacting the gap exposure measure (in percentage points) with indicators for months relative to the increase. Event time is measured relative to September 2022, the omitted reference period; the increase took effect in October 2022, so $k = 1$ is the first treated month. Fixed effects as in specification (2). Every panel refers to a different outcome variable. Vertical bars show 95 percent confidence intervals based on standard errors clustered at the labor-market-region level. N = 349,843.

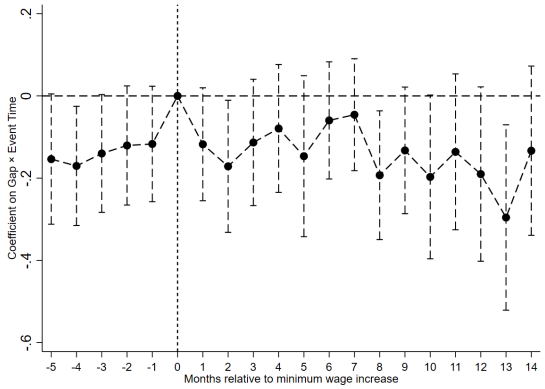
Figure A6: Event studies on the *skill diversity* by skill category (saturated FE specification)



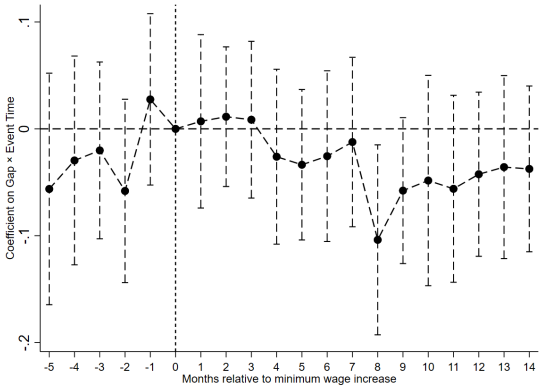
(a) Cognitive skills



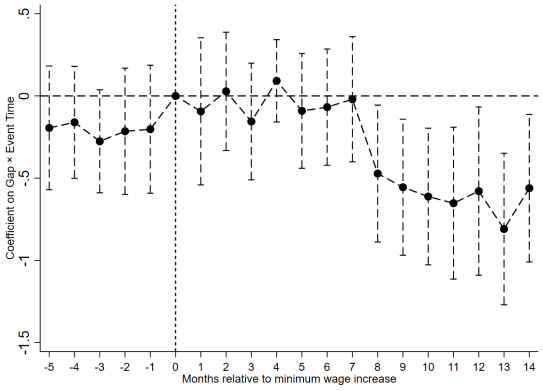
(b) Digital skills



(c) Manual Skills



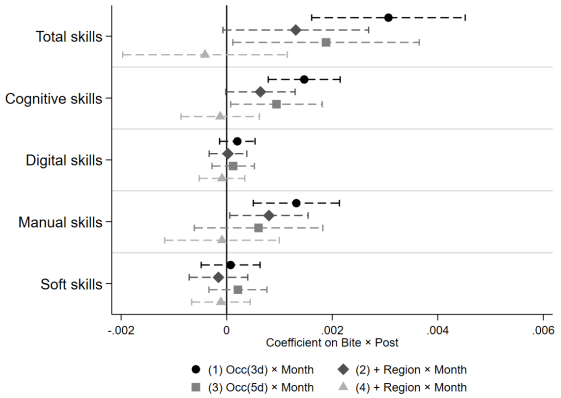
(d) Soft skills



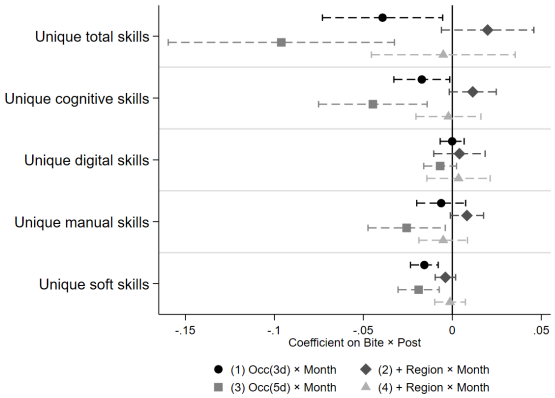
(e) Sum of skills

Notes: The figure plots the coefficients β_k from equation (10), interacting the gap exposure measure (in percentage points) with indicators for months relative to the increase. Event time is measured relative to September 2022, the omitted reference period; the increase took effect in October 2022, so $k = 1$ is the first treated month. Fixed effects as in specification (4). Every panel refers to a different outcome variable. Vertical bars show 95 percent confidence intervals based on standard errors clustered at the labor-market-region level. N = 349,843.

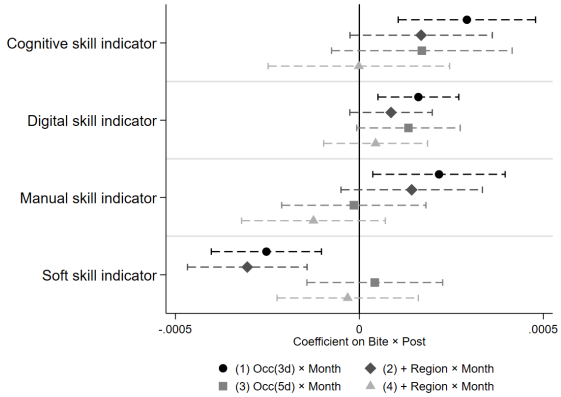
Figure A7: Effect of bite exposure on the set of skill outcomes



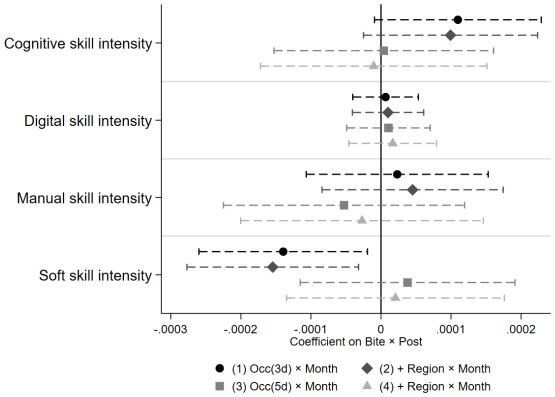
(a) Skill quantity



(b) Skill diversity



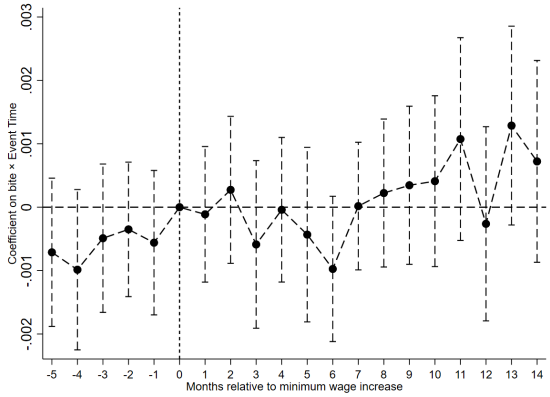
(c) Skill incidence



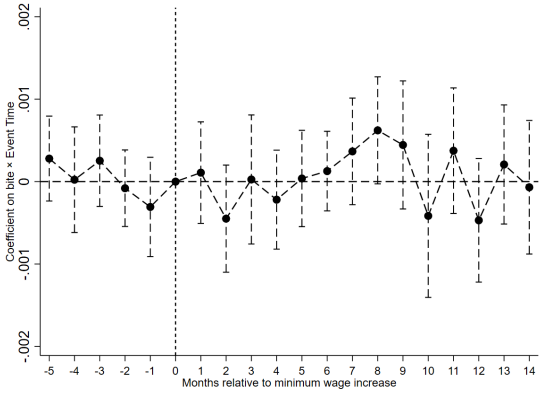
(d) Skill composition

Notes: The figure reports coefficients on the interaction of the bite exposure measure with the post-October-2022 indicator, from separate regressions by outcome. Every panel reports a different outcome category. The bite is measured in percentage points. Specifications differ in their time controls, as indicated in the legend; all include occupation (5d) × labor-market-region fixed effects. Horizontal bars show 95 percent confidence intervals based on standard errors clustered at the labor-market-region level. N = 270,157.

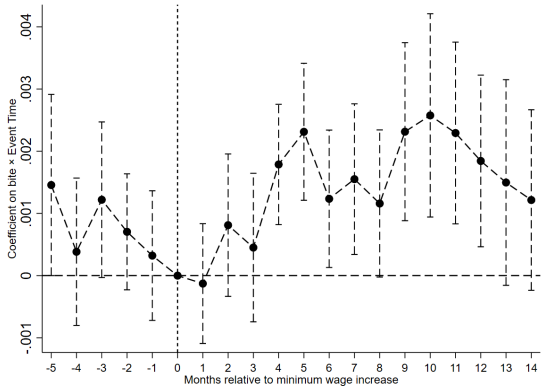
Figure A8: Event studies on *skill quantity* using bite exposure



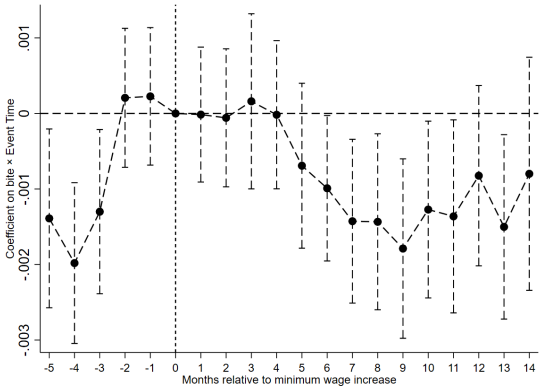
(a) Cognitive skills



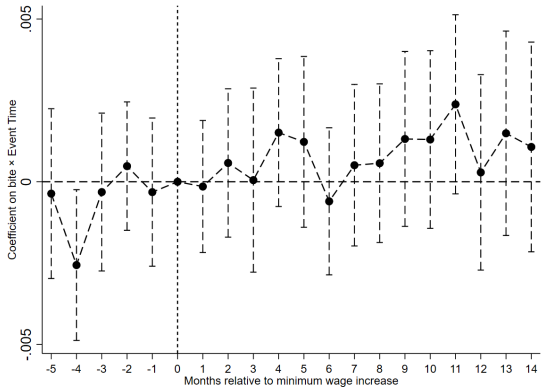
(b) Digital skills



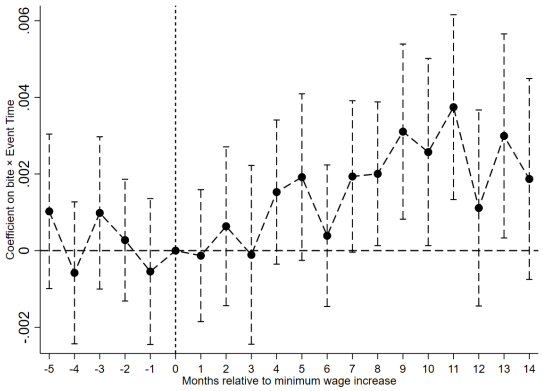
(c) Manual Skills



(d) Soft skills



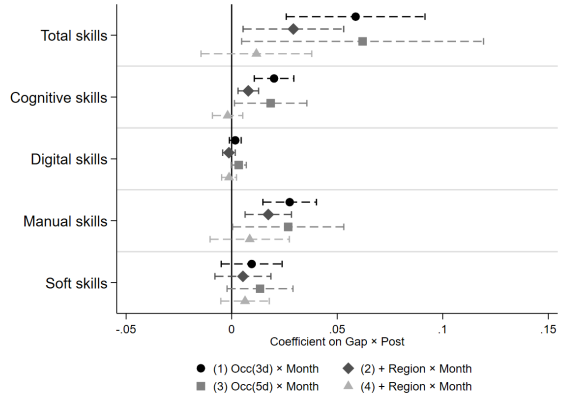
(e) Sum of skills



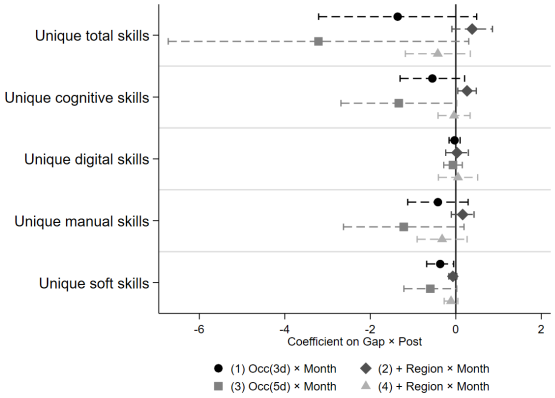
(f) Sum of skills (without soft)

Notes: The figure plots the coefficients β_k from equation (10), interacting the bite exposure measure (in percentage points) with indicators for months relative to the increase. Event time is measured relative to September 2022, the omitted reference period; the increase took effect in October 2022, so $k = 1$ is the first treated month. Fixed effects as in specification (2). Every panel refers to a different outcome variable. Vertical bars show 95 percent confidence intervals based on standard errors clustered at the labor-market-region level. N = 270,157.

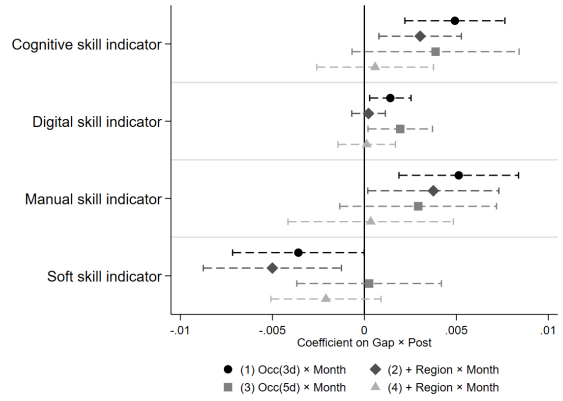
Figure A9: Effect of gap exposure on the set of skill outcomes using a Federal State aggregation



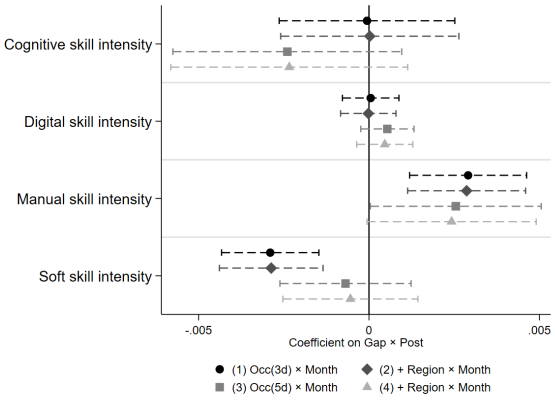
(a) Skill quantity



(b) Skill diversity



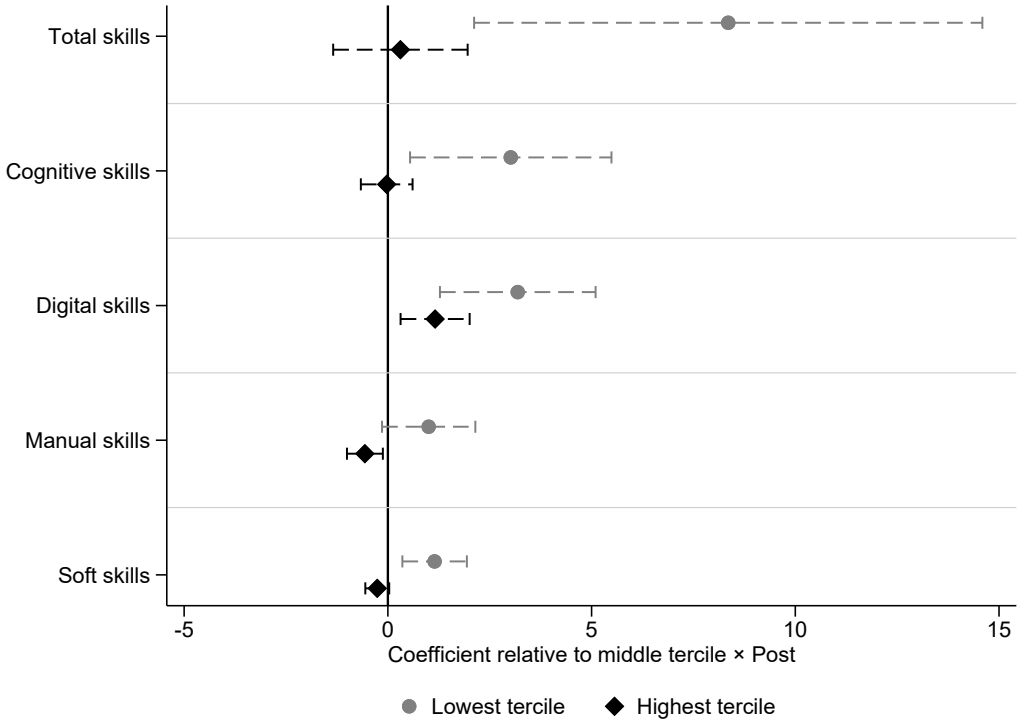
(c) Skill incidence



(d) Skill composition

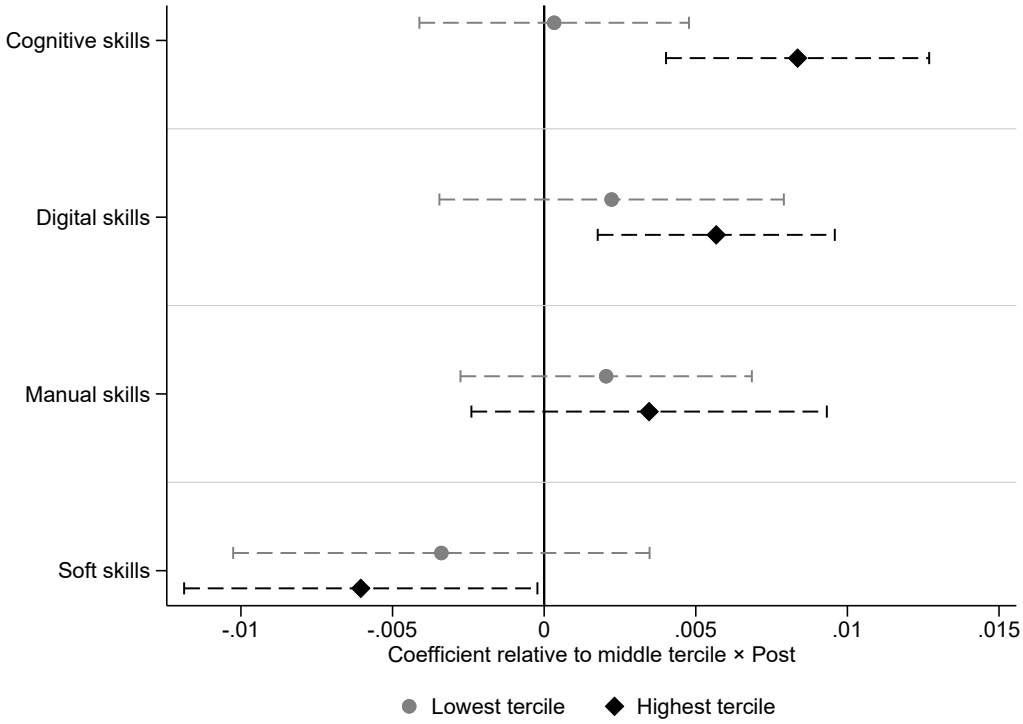
Notes: The figure reports coefficients on the interaction of the gap exposure measure with the post-October-2022 indicator, from separate regressions by outcome. Every panel reports a different outcome category. The gap is measured in percentage points. Specifications differ in their time controls, as indicated in the legend; all include occupation (5d) × federal state fixed effects. Horizontal bars show 95 percent confidence intervals based on standard errors clustered at the federal state level. N = 81,562.

Figure A10: Effect of gap exposure on *skill diversity* by exposure tercile



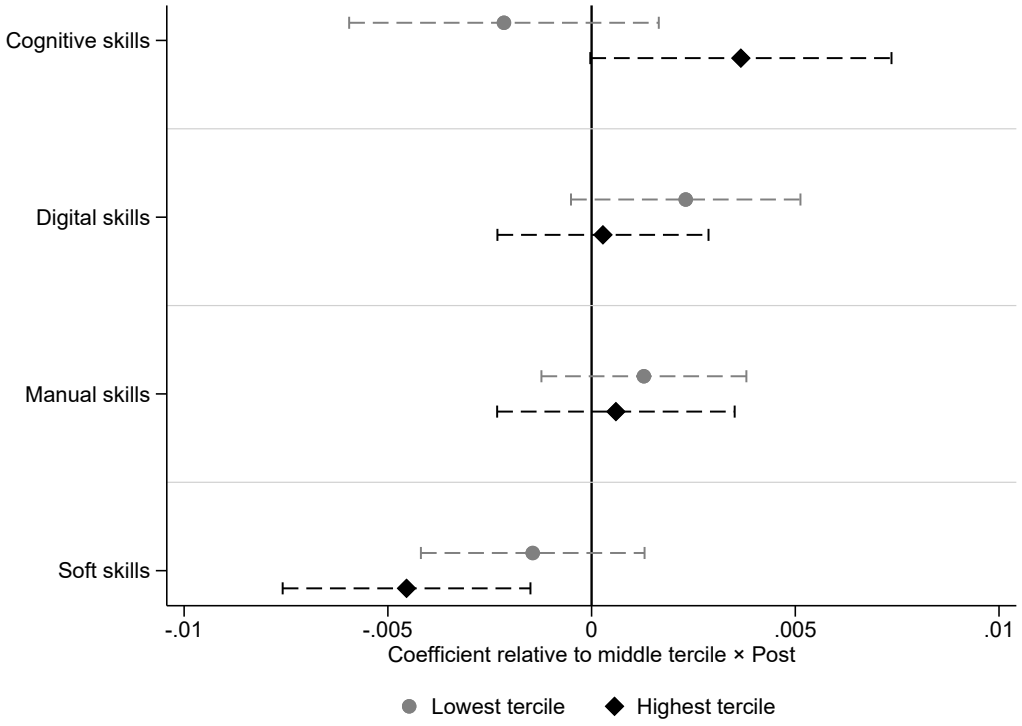
Notes: The figure reports coefficients on the interactions of the post-October-2022 indicator with indicators for the bottom and top terciles of the gap distribution; the middle tercile is the omitted reference group. Each coefficient therefore gives the differential post-reform change in the respective group relative to cells of intermediate exposure. Outcomes are the number of unique skill mentions in an occupation–labor-market-region cell. Fixed effects as in specification (2). Horizontal bars show 95 percent confidence intervals based on standard errors clustered at the labor-market-region level. N = 349,843.

Figure A11: Effect of gap exposure on *skill incidence* by exposure tercile



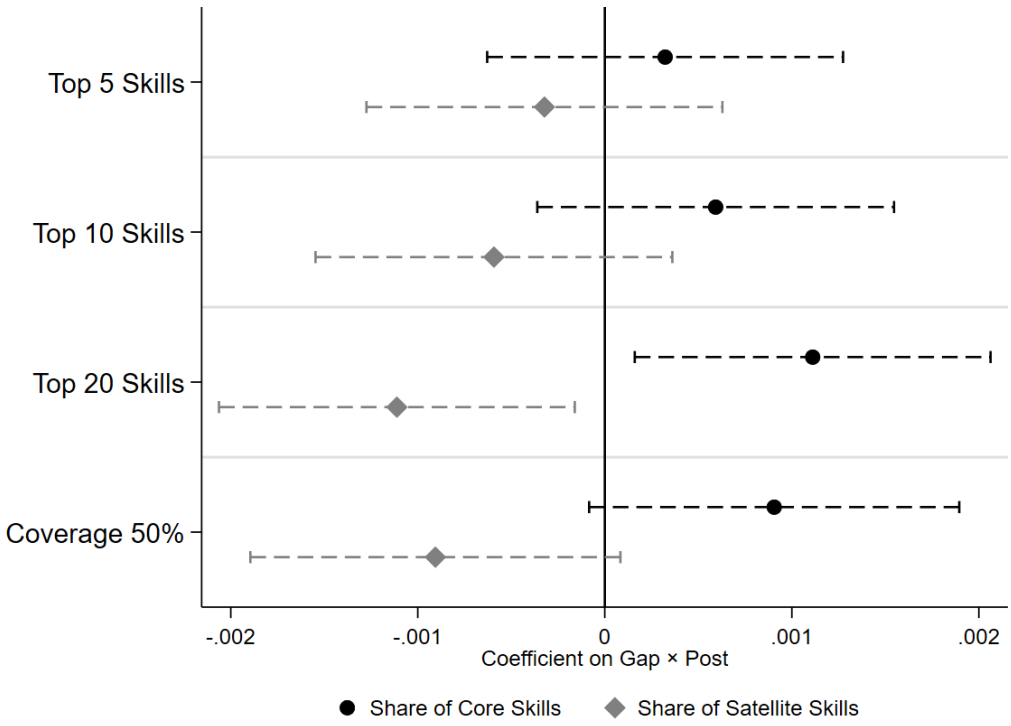
Notes: The figure reports coefficients on the interactions of the post-October-2022 indicator with indicators for the bottom and top terciles of the gap distribution; the middle tercile is the omitted reference group. Each coefficient therefore gives the differential post-reform change in the respective group relative to cells of intermediate exposure. Outcomes are the shares of postings in an occupation–labor-market-region cell that require at least one skill from the respective category. Fixed effects as in specification (2). Horizontal bars show 95 percent confidence intervals based on standard errors clustered at the labor-market-region level. N = 349,843.

Figure A12: Effect of gap exposure on *skill composition* by exposure tercile



Notes: The figure reports coefficients on the interactions of the post-October-2022 indicator with indicators for the bottom and top terciles of the gap distribution; the middle tercile is the omitted reference group. Each coefficient therefore gives the differential post-reform change in the respective group relative to cells of intermediate exposure. Outcomes are the respective share of the task group for the overall task demand for postings in an occupation–labor-market-region cell. Fixed effects as in specification (2). Horizontal bars show 95 percent confidence intervals based on standard errors clustered at the labor-market-region level. N = 349,843.

Figure A13: Effect of gap exposure on the share of core and satellite skills (saturated FE specification)



Notes: The figure reports coefficients on the interaction of the gap exposure measure (in percentage points) with the post-October-2022 indicator, under specification (4). Outcomes are the core and satellite shares of a vacancy's skill mentions; since the two sum to one, their coefficients mirror each other. Rows correspond to alternative core definitions, fixed over the 2017–March 2022 window. Horizontal bars show 95 percent confidence intervals, clustered at the labor-market-region level. N = 349,843.

B Tables

Table B1: Most exposed occupation groups weighted by employment

	Gap Measure			Bite Measure		
Rank	Occupation	Gap	*N*	Occupation	Bite	*N*
1	Occupations in cleaning services (without specialisation) – helper	0.038	638,754	Occupations in cleaning services (without specialisation) – helper	0.562	638,754
2	Sales occupations in retail trade (without product specialisation) – skilled worker	0.020	912,679	Occupations in warehousing and logistics – helper	0.329	952,401
3	Occupations in warehousing and logistics – helper	0.019	952,401	Professional drivers (passengers transport) – skilled worker	0.327	864,746
4	Professional drivers (passengers transport) – skilled worker	0.021	864,746	Sales occupations in retail trade (without product specialisation) – skilled worker	0.307	912,679
5	Gastronomy occupations (without specialisation) – helper	0.061	201,030	Office clerks and secretaries (without specialisation) – skilled worker	0.147	1,521,756
6	Cooks (without specialisation) – helper	0.050	236,424	Cooks (without specialisation) – helper	0.535	236,424
7	Office clerks and secretaries (without specialisation) – skilled worker	0.006	1,521,756	Gastronomy occupations (without specialisation) – helper	0.627	201,030
8	Gastronomy occupations (without specialisation) – skilled worker	0.043	205,145	Sales occupations (retail) selling foodstuffs (without specialisation) – skilled worker	0.404	266,306
9	Occupations in hairdressing – skilled worker	0.067	119,825	Gastronomy occupations (without specialisation) – skilled worker	0.519	205,145
10	Sales occupations (retail) selling foodstuffs (without specialisation) – skilled worker	0.028	266,306	Office clerks and secretaries (without specialisation) – helper	0.381	215,507

Notes: Occupations are ordered according to their employment-weighted rank in the underlying exposure distribution. Exposure measures are computed as employment-weighted averages for Germany as a whole. *N* denotes the total number of individuals working in that occupation in 2022 as per the occupational panel.