Skills Mismatches and Worker Mobility

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Skills Mismatches and Worker Mobility*
Scientific Progress Report

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Abstract

This report studies the role of mismatch for the effects of updating vocational curricula on early-career outcomes in Germany's dual system. Linking training regulations to administrative worker records, patent-based technology exposure, and survey-based mismatch measures, it exploits curriculum revisions in a stacked difference-in-differences design. Updates raise entrants' daily wages by up to 4.1 percent and reduce occupational mobility by up to 4.7 percentage points. Wage gains are larger in technology-exposed occupations. High prior mismatch is associated with particularly strong occupational mobility effects. In contrast, updates do not result in higher wages when the previous curriculum was neither exposed to new technologies nor characterized by high mismatch. This indicates that curriculum updates benefit early-career workers when they are required due to either mismatch of the old curriculum or changing job requirement due to new technologies.

Keywords: Vocational education, technological change, skill mismatch, curriculum updates
JEL codes: J25, J24, O33

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1 Introduction

This report documents the scientific progress achieved under Task 5.4 of the Horizon Europe SkiLMeeT project, which investigates skills mismatches between supply and demand, and worker mobility. The central aim of this task is to explore the role of skills gaps and mismatches for workers' labour-market careers, examining how the alignment or misalignment between vocational training curricula and evolving occupational skill requirements shapes wage trajectories and occupational transitions. Task 5.4 seeks to analyse the consequences of curriculum updates for workers, with particular attention to heterogeneity by technology exposure and prior skill mismatch. This report presents the empirical findings from the accompanying scientific research paper Salomons et al. (2025), which traces a complete causal chain from technological change to curriculum content to worker outcomes, and situates these findings within the broader objectives of the SkiLMeeT project. The basic analytical strategy pursued in this work builds upon the novel database of legally binding training curricula spanning the near-universe of vocational training in Germany over five decades, linked to patent-based measures of technological progress and administrative employer-employee records (Salomons et al., 2025).

The research examines whether curriculum updates support workers in coping with new technologies at the workplace by studying how workers' wages and occupational retention respond for those who acquire newly emerging competencies. The analysis splits results by technology exposure to identify whether curriculum updates are particularly valuable when occupations face rapid technological change, and investigates the role of prior skill mismatch in moderating returns to skill updating. The results show that curriculum updates reduce the tendency of labour-market entrants to leave their training occupation, with this occupational-retention effect particularly pronounced where pre-update mismatch is high. In contrast, wage returns do not increase monotonically with the available measure of prior mismatch. Rather, wage gains reflect the joint role of mismatch and technological change: in occupations with relatively low measured mismatch, updates generate substantial wage returns primarily when they are exposed to new technologies, whereas in high-mismatch occupations updates yield wage gains under both low and high technology exposure. Taken together, these findings suggest that curriculum revisions operate both by restoring the fit between training and occupational requirements and by equipping workers with newly valuable expertise in changing labour markets.

The empirical analysis presented in this report build on the data generated in Deliverable

2.10 of the SkiLMeeT project Salomons et al. (2025). The present text constitutes the formal Task 5.4 progress reporting. The results from our scientific research are used in our accompanying scientific research paper Salomons et al. (2025), which provides comprehensive technical details, robustness checks, and extended analyses. This report presents Task 5.4 results under the SkiLMeeT project, documenting the activities and findings produced in fulfilment of the task's objectives. Our accompanying scientific research paper combines the research conducted across several SkiLMeeT project tasks into a broader analysis that extends beyond the project's immediate reporting requirements. The paper provides the full methodological apparatus, extensive robustness checks, and detailed appendices that underpin the summary findings presented here. Throughout this report, we cite the main paper using the standard academic format and provide cross-references to specific sections, tables, and figures where readers can locate technical details.

Our findings contribute to four strands of the literature. A first strand studies how the gap between a worker's skills and the requirements of the job affects wages, mobility and career progression (Guvenen et al., 2020; Lise and Postel-Vinay, 2020; Fredriksson et al., 2018; Deming and Noray, 2020; Braxton et al., 2021; Storm, 2023; Agrawal et al., 2025). Three findings recur. Mismatch is multidimensional, so what matters is the fit of the whole skill portfolio rather than the level of qualification. Mismatch is associated with lower entry wages and greater mobility, with consequences particularly salient early in workers' careers (Fredriksson et al., 2018). And mismatch leaves scarring effects: Dynamic models of multidimensional skills imply that poor initial matches can have persistent consequences for subsequent human-capital accumulation and wages (Guvenen et al., 2020; Lise and Postel-Vinay, 2020). This literature typically examines mismatch at the worker–job level. Our analysis instead considers an earlier margin: the alignment between the curriculum and the occupational requirements. We exploit discrete, legally binding curriculum revisions in the German dual system to study whether updating training content affects early-career outcomes. This contributes by studying whether reducing the skill gap at the point of training produces measurable career gains, and whether those gains are concentrated where the gap was largest.

Second, we contribute to work on job displacement and occupational mobility, which establishes that the cost of a career transition is set by the distance the worker has to travel in skill space (Poletaev and Robinson, 2008; Gathmann and Schoenberg, 2010; Gathmann et al., 2020; Andersson et al., 2018; Huckfeldt, 2022; Schmieder et al., 2023; Neffke et al., 2024; Hanushek et al., 2025; Tian, 2025; Ziya Sen, 2025). Human capital is neither general

nor firm-specific but task-specific, and losses after a move track the change in the skill portfolio rather than the change in occupation or industry code (Poletaev and Robinson, 2008; Gathmann and Schoenberg, 2010). Most directly, Neffke et al. (2024) show for Germany that displacement raises the probability of occupational change elevenfold, and that workers who move into jobs which make their skills redundant are set on a permanently lower earnings path, while those who move into jobs demanding more eventually recover. Two further findings shape our design. (Schmieder et al., 2023) document substantial post-displacement earnings losses and analyse their sources, motivating attention to employer sorting and pay premia, which is why we track employer quality. Hanushek et al. (2025) emphasize substantial heterogeneity in post-displacement adjustment that is not fully accounted for by standard observables. Our contribution to this literature is not to study adjustment after an exogenous displacement event, but to examine a policy margin that may shape occupational adjustment before workers enter their careers: the updating of vocational training content.

Third, our work speaks to the literature on vocational education and worker careers, and in particular to the debate over what vocational training buys and what it costs (Dustmann and Schönberg, 2012; Fitzenberger et al., 2015; Hanushek et al., 2017; Eggenberger et al., 2018; Kiener et al., 2022; Langer and Wiederhold, 2023; Cnossen et al., 2025). The central result is a trade-off over the life cycle: vocational training raises employment early and lowers it later, and the reversal is sharpest in apprenticeship countries including Germany (Hanushek et al., 2017).Greater occupational specificity in vocational curricula is associated with higher wages and lower occupational mobility (Eggenberger et al., 2018). A related body of work shows that the content of curricula can be read directly from their text and priced (Kiener et al., 2022; Langer and Wiederhold, 2023; Cnossen et al., 2025), and that among German apprenticeship graduates the type of move matters, since occupation changes within the training firm raise wages while moves that break both the firm and the occupation tie do not (Fitzenberger et al., 2015). This literature treats curriculum content as fixed and asks what it is worth. We treat it as something that changes, and ask what happens to careers when it does. One possible interpretation of the later-life disadvantage documented by Hanushek et al. (2017) is that occupation-specific skills become less adaptable as task requirements change. If that reading is correct, then updates which close a large skill gap should produce exactly the career gains we look for. We contribute by exploiting changes in nationally standardised curriculum content to estimate how curriculum updating affects the early careers of successive apprentice cohorts trained for the same occupation.

Fourth, we contribute to work on technology shocks, educational content and worker

adjustment (Janssen and Mohrenweiser, 2018; Kelly et al., 2021; Dauth et al., 2021; Biasi and Ma, 2023; Battisti et al., 2023; Conzelmann et al., 2023; Di Giacomo and Lerch, 2026; Kogan et al., 2023; Light, 2024; Schultheiss and Backes-Gellner, 2024; Buehler et al., 2025; Dillon et al., 2025; Salomons et al., 2025). Two results frame our exercise. First, whether a technology shock harms a worker depends on whether training is available. (Battisti et al., 2023) show that technological and organisational change is associated with worker reallocation and training; average earnings consequences vary across workers, with older workers more adversely affected. Dauth et al. (2021) show that labour-market adjustment to robots occurs through several margins, including task and employment reallocation; this motivates attention to entrants as well as incumbents. That places the content of entry-level training at the centre of the adjustment process. Second, educational content does adjust to demand, but slowly and unevenly, whether measured as the distance between syllabi and the research frontier (Biasi and Ma, 2023), as the response of degree programmes to job postings (Conzelmann et al., 2023; Light, 2024), or as the response of vocational curricula to breakthrough patents (Salomons et al., 2025). Closest to us, Janssen and Mohrenweiser (2018) trace one German curriculum reform over 25 years and show that it lowers incumbents' wages while advantaging the new cohort, and Buehler et al. (2025) show that the wage effect of a Swiss update depends on what kind of skill it adds. We extend this evidence by linking curriculum revisions in the near-universe of German dual-system training occupations to workers' subsequent early-career outcomes, in particular wages, annual earnings, and occupational, industry, and firm mobility. We link these effects to technology exposure and to measured training–work mismatch. This evidence highlights curriculum updating as one institutional mechanism through which vocational education can respond to changing skill demand.

The rest of this report is structured as follows: Section 2 presents the datasets and indicators on vocational training curricula updates, technology exposure, worker careers and skill mismatch. Section 3 provides our empirical strategy and key results. We conclude in Section 4.

2 Data

This section summarises the principal data sources underlying the empirical analysis. The research design relies on three interconnected datasets: vocational training curricula and their updates, patent-based measures of technology exposure, and administrative employer-

employee records tracking workers' labour-market outcomes. These three datasets are the output of Deliverable 2.6 of the SkiLMeeT project (Salomons et al., 2025). A fourth data source, the Qualification and Career Surveys, provides supplementary information on skill mismatch and self-reported training usefulness. Full methodological details on data construction, variable definitions, and sample restrictions for the first three datasets are provided in the main paper and in Deliverable 2.6 of the SkiLMeeT project (Sections 2 and 4.1 Salomons et al., 2025); the description below therefore remains at a summary level sufficient for understanding the empirical strategy and results.

2.1 Vocational Training Curricula

The analysis exploits a novel database of legally binding training curricula for the German dual vocational training system, constructed by web-scraping the archives of the Federal Law Gazette (Bundesgesetzblatt) and covering the period from 1971 to 2021. In Germany, vocational training typically combines classroom schooling (one to two days weekly) with on-the-job training at a firm (three to four days weekly), and is undertaken as a full-time programme typically lasting three years after high school. Following the 1969 Vocational Training Act (Bundestag, 1969), virtually all dual training is codified in state-approved and nationally standardised training curricula, which are regularly revised through a well-defined and institutionalised process involving employer associations, labour unions, and the Federal Institute for Vocational Education and Training (BIBB). The parties involved have agreed to limit the duration of the revision process to approximately one year, with an additional six months until legal enactment, such that curriculum updates arrive around 1.5 years after official initiation (Federal Institute for Vocational Education and Training (BIBB), 2020). This institutionalised updating process is initiated by employers, employees, or BIBB itself, and results in legally binding documents that specify the obligations and rights of both trainees and trainers, including detailed descriptions of the skills and knowledge to be acquired during the programme.

The database comprises 756 unique training curricula characterising 492 training occupations, with each curriculum averaging 11.1 pages of elaborate textual description specifying the skills, knowledge, and examination requirements for each occupation. Curricula are machine-translated from German to English to enable Natural Language Processing (NLP) linkage to patent texts. The training occupations link to 237 distinct official occupation codes from the 2010 German classification system (Klassifikation der Berufe, KldB) at the 4-digit level, using a crosswalk provided by BIBB. This setting covers a substantial share of

the labour market: vocationally trained workers constitute approximately 70 percent of the German workforce over the sample period, more than five times the 12 percent share with a university degree, and are concentrated in middle-wage occupations that have been most exposed to task automation over the past decades. The curriculum data reveal substantial heterogeneity in update frequency across occupations: among curricula that are eventually updated, the average interval between updates is 15.3 years, though this varies considerably, with some curricula updated within a few years while others remain unchanged for two or more decades. Occupations in IT and scientific services update most frequently, followed by business services, production, and other commercial services, while personal service occupations update least frequently.

Curriculum updates occur for a wide variety of reasons, as documented by BIBB-provided data on update applications since 2011 covering 135 update proposals. Technological change is the most commonly cited substantive reason, mentioned 115 times across the 135 proposals, with digitisation specifically cited in 32 cases. Changes in competences are mentioned 97 times, encompassing both growth and decline of competences, while firm-level structural change appears 40 times. Procedural and administrative reasons, such as changes to examination format or occupational delimitations, are also frequently cited. This diversity of update motivations is important for interpreting the heterogeneity analysis presented below, as not all curriculum updates are driven by technological advances; some reflect procedural adjustments or changes in firm organisation that may have different implications for worker outcomes.

2.2 Technology Exposure

Technology exposure is measured using U.S. utility patents classified as technological breakthroughs, following the classification developed by Kelly et al. (2021). These breakthroughs are identified as patents that are both novel—distinct from previous patents—and influential for subsequent innovation—similar to later patents—operationalised as the top 10 percent of patents by year in terms of forward-to-backward textual similarity. The analysis focuses on the subset of breakthrough patents in digital technologies, which have seen the largest expansion over the sample period and comprise the majority of all patenting towards the end of the period, reflecting the Digital Revolution. Breakthrough patents are lagged by 20 to 25 years relative to the curriculum data, considering technological breakthroughs occurring over 1946 to 2001 for the 1971 to 2021 curriculum period. This lag reflects the delay between the patenting of a high-level breakthrough and the follow-on innovations through which it is

eventually applied in production, following the approach of Autor et al. (2024), who use the same lag length for measuring occupational exposure to breakthrough patents.

Each training occupation's technology exposure is measured by linking each curriculum in year t to the textual content of breakthrough patents emerging over the five-year window [t-25, t-20]. The linkage employs Natural Language Processing techniques rather than keyword searches, as curricula describe skills and tasks rather than technologies by name. Specifically, the method computes Term-Frequency Inverse-Document-Frequency (TF-IDF) weighted averages of pre-trained word embedding vectors (Pennington et al., 2014) for verbs and nouns in both curricula and patents, then obtains the cosine similarity between every patent-curriculum pair. These similarity scores are normalised by subtracting the median similarity for each patent to avoid assigning low similarities to patents using more technical language, following Autor et al. (2024). The 15 percent most similar patent-curriculum pairs are retained and summed for each curriculum, yielding an occupational patent count that serves as the measure of technology exposure. This procedure is performed separately for all patents and for the subset of digital patents, with the latter serving as the baseline measure.

The resulting technology exposure measure exhibits substantial variation across occupations. Digital technology exposure has a standard deviation of approximately 2.58 in the unweighted panel and 2.61 in the employment-weighted panel. Training occupations with high exposure include various types of electronics technicians, industrial mechanics, cutting machine operators, plant mechanics, and tool mechanics, while jobs with low exposure include various service occupations such as factory firemen, ice cream specialists, and bespoke shoemakers, as well as production occupations like leather production specialists, candle makers, and concrete manufacturers. The patent-based technology exposure measure finds direct support in the subsample where stated reasons for curriculum updates are observed: among the 137 updates over 2011 to 2021, 40 percent cite technological change as a reason, of which 15 percent specifically cite digitisation, and updates citing digitisation have significantly higher digital technology exposure than other updates, confirming that occupations identified as highly exposed to digital technology by the patent-based measure are indeed updating in response to digitisation.

2.3 Workers' Careers

The analysis of labour-market outcomes employs SIEED (Sample of Integrated Employer-Employee Data), a 1.5 percent random sample of German firms with linked employee information from administrative records provided by the Institute for Employment Research

(IAB) at the Federal Employment Agency (Berge et al., 2020). The data contain all workers ever employed by sampled firms plus pre-estimated AKM firm fixed effects (Abowd et al., 1999), enabling analysis of both worker outcomes and firm pay premia. For these workers, complete employment biographies are observed between 1975 and 2018, including wages, occupation, industry, and location of employing firms, as well as apprenticeship training spells indicating when workers start and complete their training programme and which occupation they train in. Combined with the curriculum dataset, this allows determination of which curriculum vintage each worker was trained in, a feature that is infeasible in most educational systems where training content decisions are uncodified or decentralised. The SIEED dataset contains 5.6 million unique workers and 173 million employment spells, providing sufficient statistical power for the event-study analyses described below.

We construct a dataset of labour-market entrants, defined as vocationally trained workers observed in the first five years after completing their apprenticeship. The sample is restricted to workers whose training curriculum is observed, dropping workers trained before the start of the curriculum data in 1975 and workers not trained in West Germany, as training curricula before German reunification apply only to West German apprentices. This entrant sample contains 3,276,736 worker-year observations, with workers averaging 23.3 years of age, 40 percent female, and daily wages averaging 66.64 euros with a standard deviation of 30.83 euros. Most workers are employed year-round, with a median of 365 days in employment, and work in relatively large firms averaging 560 workers, though the median firm size is 40 workers reflecting the firm-based sampling design. Baseline occupational mobility, measured relative to the apprenticeship position, is 37 percent over the first five years after graduation, while industry and firm mobility are 42 percent and 62 percent respectively (Table 1).

2.4 Skill Mismatch

Skill mismatch is measured using the Qualification and Career Surveys (QCS) conducted by BIBB, the Federal Institute for Occupational Safety and Health (BAuA), and IAB across seven waves spanning 1979, 1986, 1992, 1999, 2006, 2012, and 2018. These representative surveys of the German labour force include questions on workers' self-reported usefulness of their vocational training for their current work tasks, which serves as an inverse measure of skill mismatch between the training curriculum and actual work demands. The surveys also contain information on workers' training occupation and training year, enabling assignment of workers to their specific training curriculum vintages. The usefulness measure is reported on a scale from 0 to 100, with higher values indicating greater perceived relevance of training

Table 1: Descriptives of Vocationally Trained Labor Market Entrants

	Mean	SD	Median
Age	23.27	3.03	23.00
Year of birth	1975	9.63	1975
Female	0.40	0.49	0.00
Average daily wage (euros)	66.64	30.83	66.56
Annual daily wage growth	0.13	0.48	0.07
Years of training	2.82	0.53	2.88
Annual days employed	268	139	365
Annual labor earnings (euros)	18,249	13,611	18,367
Firm size	560	2,758	40
Job mobility, relative to apprenticeship:			
Occupation	0.37	0.48	0.00
Industry	0.42	0.49	0.00
Firm	0.62	0.48	1.00
Job mobility, year-to-year:			
Occupation	0.19	0.39	0.00
Industry	0.20	0.40	0.00
Firm	0.30	0.46	0.00

SIEED sample, full sample prior to stacking. Workers in the first five years after graduation with a training duration between 1.75 and 4.25 years, restricted to workers for whom we observe the training occupation and curriculum. $N = 3{,}276{,}736$ worker by year observations.

to current work.

We regress self-reported training usefulness on the number of years since the curriculum was last updated at the time of training:[1]

$$\text{Usefulness}_{ij\tau}^{t} = \beta \text{Years since update}_{j\tau} + \gamma_{\tau}^{t} + X_i + \delta_J + \varepsilon_{ij\tau}^{t}. \tag{1}$$

The dependent variable is the usefulness of training for worker i who completed training in training occupation j in year τ, self-reported at the time of survey wave t.[2]

Workers trained under more recently updated curricula report finding their training more useful for their current jobs: being trained in a curriculum that was last updated 15 years

[1]We keep curricula where the last update occurred at most 20 years ago: we do not observe enough survey respondents for the earlier updates.

[2]We follow Dustmann and Schoenberg (2012) and assign the following usefulness levels: very much = 90, a lot = 75, some = 50, not too much = 25, and very little = 10.

ago (the average time for a curriculum update to occur) versus a just-updated curriculum is associated with a reduction in reported usefulness of 6.2 percentage points, corresponding to 18 percent of a standard deviation in the usefulness measure (Table 2). This finding provides direct evidence that curriculum staleness generates skill mismatch, validating the use of curriculum vintage as a proxy for skill relevance.

Table 2: Training usefulness by age of training curriculum

	(1)	(2)	(3)	(4)
Years since update	-0.27*	-0.27*	-0.34**	-0.41*
	(0.12)	(0.12)	(0.12)	(0.18)
Wave × Training completion year FE	X	X	X	X
Firm size		X	X	X
1-digit occupation FE			X	
4-digit occupation FE				X

Based on Qualification and Career Survey data. Dependent variable: Self-reported usefulness of training (mean 63.3, standard deviation 34.1. Standard errors clustered by training occupation. $N = 6,854$. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

We use the inverse of this usefulness measure as an indicator of mismatch. Ideally, we would want yearly-varying occupation level information on skill mismatch. However, due to sample size restrictions, we compute average mismatch at two levels: First, we compute mismatch at the 2-digit occupation level for each year to have yearly varying information. Second, we pool all 7 waves and compute mismatch at the 3-digit occupation level. We linearly interpolate the years between the survey waves. The former measure has the advantage of yearly-varying information at the expense of occupational detail, and vice versa for the second measure. We will use both measures in our further analysis.

An alternative approach to measuring skill mismatch – which we rely on in SkiLMeeT Deliverable 4.1 (Jonas et al., 2026) – would employ job-posting data. This approach has been used in recent literature to construct multidimensional demand-side measures of occupational skill requirements (Atalay et al., 2020; Deming and Noray, 2020; Acemoglu and Restrepo, 2022). However, job-posting data are not used in this analysis for two principal reasons. First, systematic electronic collection of job vacancy data in Germany begins only in 2017 in Germany, yielding only few years of consistent data, which is insufficient for the longitudinal curriculum-linkage analysis spanning five decades that this project undertakes. Second, job-posting datasets record vacant positions and applicant flow but lack

persistent individual-level identifiers linking applicants' complete careers before and after filling positions, making them unsuitable for analysing long-term career mobility and wage trajectories. The administrative employer-employee data in SIEED, by contrast, maintain continuous person-level tracking across transitions over more than 40 years, enabling genuine mobility measurement rather than vacancy-filling counts. While job-posting data provide valuable complementary information on real-time labour demand and skill premium shifts, they cannot substitute for the longitudinal depth and individual-level career tracking that the curriculum-based analysis requires.

3 Empirical Analysis

This section examines the labour-market consequences of curriculum updates using a stacked difference-in-differences design that compares cohorts trained before and after an update with comparable cohorts in occupations without an update. We first estimate how updated curricula affect early-career wages, earnings, and occupational, industry, and firm mobility. We then assess whether these effects differ between occupations with high and low exposure to technological change. Finally, we examine whether the benefits of curriculum updating are larger when the pre-update mismatch between vocational training and occupational skill requirements is greater.

3.1 Empirical Strategy

The empirical strategy exploits the discontinuity of curriculum revision to identify causal effects of skill updates on worker outcomes. Unlike gradual shifts in skill demand, curriculum updates arrive at a specific, legally documented date, creating a sharp before-after contrast in the skill vintage that workers acquire in a given occupation. This feature enables a difference-in-differences (DiD) research design comparing workers trained under old curricula with those trained under new curricula, while controlling for secular trends using workers in occupations that did not experience updates over the same time period. We address the challenge of staggered treatment timing—different curricula update in different years—by stacking observations for different events following the approach of Cengiz et al. (2019), which has been shown to recover true treatment effects in the presence of staggered timing (Baker et al., 2022).

For our analysis, we compare cohorts of old-skilled workers (trained before a curriculum

update) and new-skilled workers (trained after) in occupations with curriculum updates against corresponding cohorts in occupations without updates over the same time window. Specifically, the analysis focuses on vocationally trained workers in the first five years after completing their training, and estimates an event-study specification where cohort c is defined by the start year of vocational training relative to the year of curriculum change, with $c = 0$ normalised to represent the first cohort trained in the new curriculum. The sample is restricted to worker cohorts whose training started in a window of five years before and five years after the treatment occupation's update ($c \in [-5, 5]$). The first difference in the DiD strategy is the difference in outcomes between old-skilled cohorts ($c < 0$) and new-skilled cohorts ($c \geq 0$) within the same occupation; the second difference is the difference in outcomes between treated workers (trained in occupations that updated) and control workers (trained in occupations that did not update over the same time window).

$$Y_{ijte} = \sum_{\substack{c=-5 \\ c\neq -1}}^{5} \beta_c \, \text{Update}_{je} \times I_{ce} + \sum_{c} \alpha_c I_{ce} + \delta_{je} + \gamma_{te} + \mu_e X_{it} + \varepsilon_{ijte} \ , \tag{2}$$

For each curriculum update event e, the analysis draws all treated workers and a random sample of control workers four times as large, with a minimum of 400 control workers when fewer than 100 treated workers are observed, yielding a total of 357 curriculum update events with 280,068 unique treated workers and 314,796 unique control workers. The specification controls for cohort fixed effects, calendar year fixed effects, training occupation fixed effects, and worker characteristics (age and gender), with all control variables except cohort fixed effects interacted with event dummies as is standard in stacked designs. Standard errors are clustered at the level of treatment, namely occupation by event. Estimates can be interpreted as causal effects under three identifying assumptions: parallel trends in the absence of curriculum updates, no anticipation of the update by prospective trainees or firms, and the stable unit treatment value assumption (SUTVA). Empirical support for these assumptions is provided through tests showing no significant pre-trends in worker outcomes, no evidence of changes in trainee composition around curriculum updates in terms of prior education, age, or gender, and evidence that positive wage effects are driven by faster wage growth for treated cohorts rather than deterioration among control cohorts (for detailed results, see Appendix D in Salomons et al., 2025).

3.2 Curriculum Updates, Workers' Careers, and Technology

3.2.1 Wage Returns for New-Skilled Workers

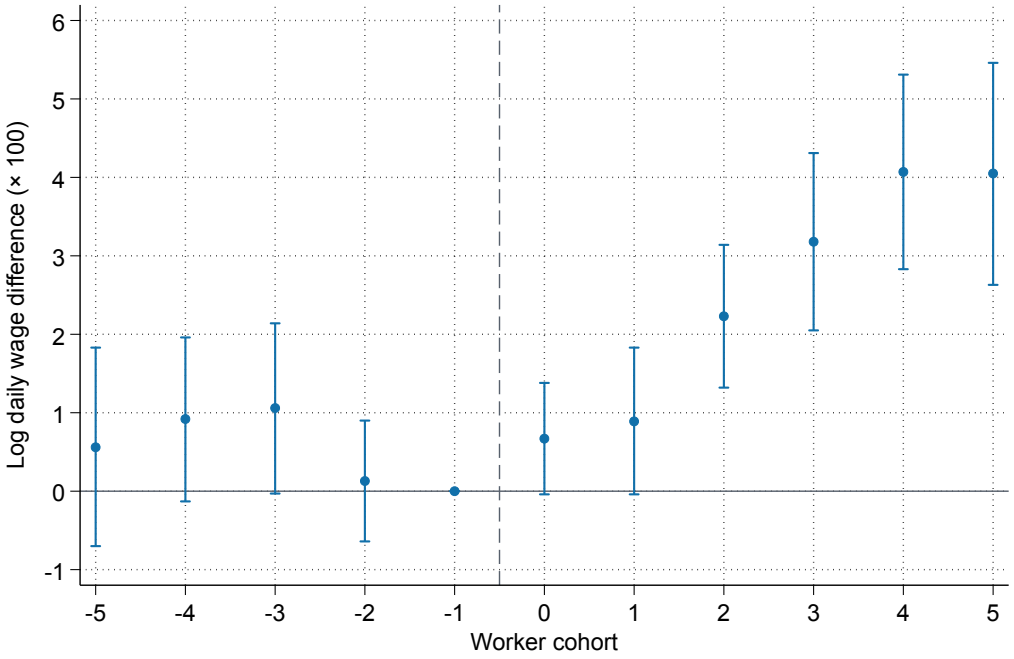
The central question for labour-market entrants is whether curriculum updates improve post-training outcomes by equipping workers with skills that are valued in the labour market. If curriculum changes enable workers to meet evolving skill demands, labour-market entrants trained with updated curricula should fare better than those trained in outdated ones. The stacked difference-in-differences analysis provides strong affirmative evidence: new-skilled workers earn substantially higher wages and remain employed in their trained occupation at higher rates than old-skilled workers in the same occupation, with these gains concentrating among curriculum updates with high technology exposure.

Figure 1 (Panel A) presents estimates of the entrant DiD specification using log daily wages as the dependent variable, with coefficients multiplied by 100 for legibility. The figure reveals no evidence of pre-trends, with a Wald test on the joint significance of pre-treatment coefficients yielding $p = 0.25$, consistent with treated and control cohorts following similar wage trajectories before curriculum reforms. Following the curriculum update, however, substantial wage returns emerge and grow across cohorts: relative to a control group of graduates in occupations without a curriculum update, new-curriculum graduates trained in the treated occupation earn up to 4.1 percent higher daily wages than old-curriculum graduates trained in the same occupation, with the maximum effect observed for cohort 5 (workers whose training started five years after the curriculum update). These are workers trained for the same occupation under the same institutional conditions—the only difference is the curriculum vintage — and this magnitude is economically meaningful, comparable to the 4.2 percent wage gain from one additional year of labour-market experience among these vocationally trained labour-market entrants, as estimated from a regression of individual log daily wages onto years of potential experience, controlling for firm AKM effects, part-time jobs, type of employment, and worker fixed effects.

The positive wage returns indicate that curriculum updates equip graduates with skills that are valued in the labour market, and these gains reflect absolute improvements in wage trajectories rather than merely relative advantages. Analysis of cohort coefficients for treated and control group workers separately demonstrates that wage returns result from more rapid wage growth for treated worker cohorts after the curriculum update, not slower wage growth for control group workers (Figure 2). This pattern is important for interpreting the results: the gains to new-skilled workers do not come at the expense of comparison cohorts, ruling

Figure 1: Entrant Wage and Earnings Impacts of Curriculum Updates

A. Log Daily Wage



B. Log Annual Earnings

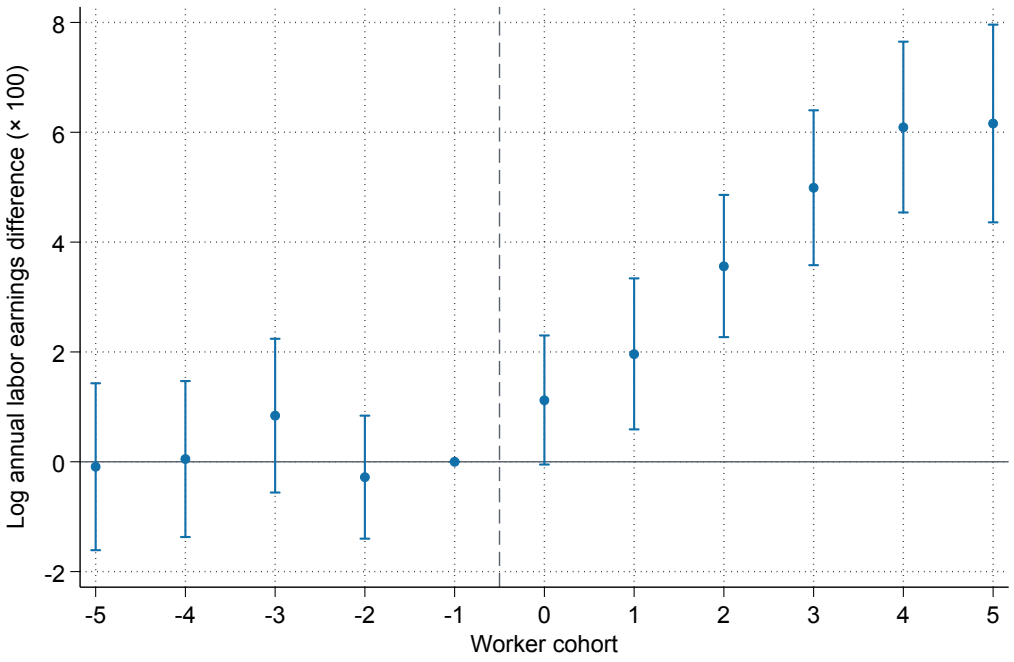


Figure reports stacked difference-in-differences estimates of equation (2), and 95% confidence intervals. Cohort 0 is the first cohort with the new curriculum; cohort -1 is the reference category. Individuals are included up to five years after graduation. Standard errors clustered at the level of occupation by event. $N = 8,969,033$ and 357 events for both panels. A Wald test of the joint significance of the coefficients for cohorts < -1 yields $p = 0.25$ for panel A and $p = 0.37$ for panel B.

Figure 2: Cohort Coefficients for Treated and Control Group Entrant Workers

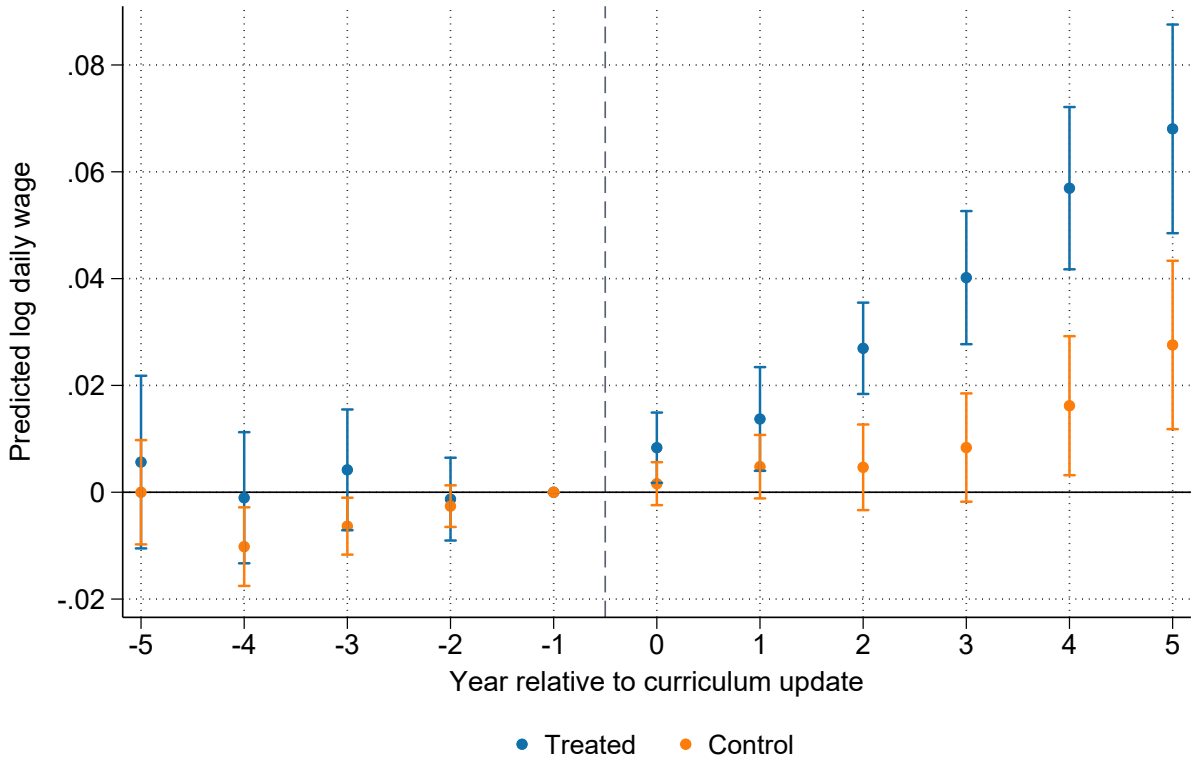


Figure reports cohort coefficients for treated ($\alpha_c + \beta_c$) and control group workers (α_c) using the stacked difference-in-differences estimate of equation (2) for log daily wages. To net out a common linear trend, we subtract a linear trend anchored at $c = -1$ for both treated and control worker cohorts, extrapolated using the average yearly change in control workers' coefficients over $c = -5$ to $c = -1$. The horizontal line at zero thus represents the counterfactual continuation of this control-group trend over the pre-period; deviations from zero indicate wage changes beyond what the extrapolated pre-period trend would predict.

out concerns about violations of the stable unit treatment value assumption that would arise if curriculum updates in treated occupations negatively affected workers in control occupations. Annual earnings effects mirror the daily wage findings, implying that effects are predominantly driven by the wage rather than employment margin, which is unsurprising given the high labour force attachment of these labour-market entrants (Figure 1, Panel B).

The wage returns are robust to a comprehensive battery of checks addressing potential threats to causal identification. Extensive analysis using data covering the universe of vocational trainees documents that curriculum updates do not impact occupational trainee composition in terms of prior high school education type, age, or gender, suggesting that wage increases are not driven by improvements in trainee characteristics following curriculum

Figure 3: Impacts of Curriculum Updates on Training Firm Composition

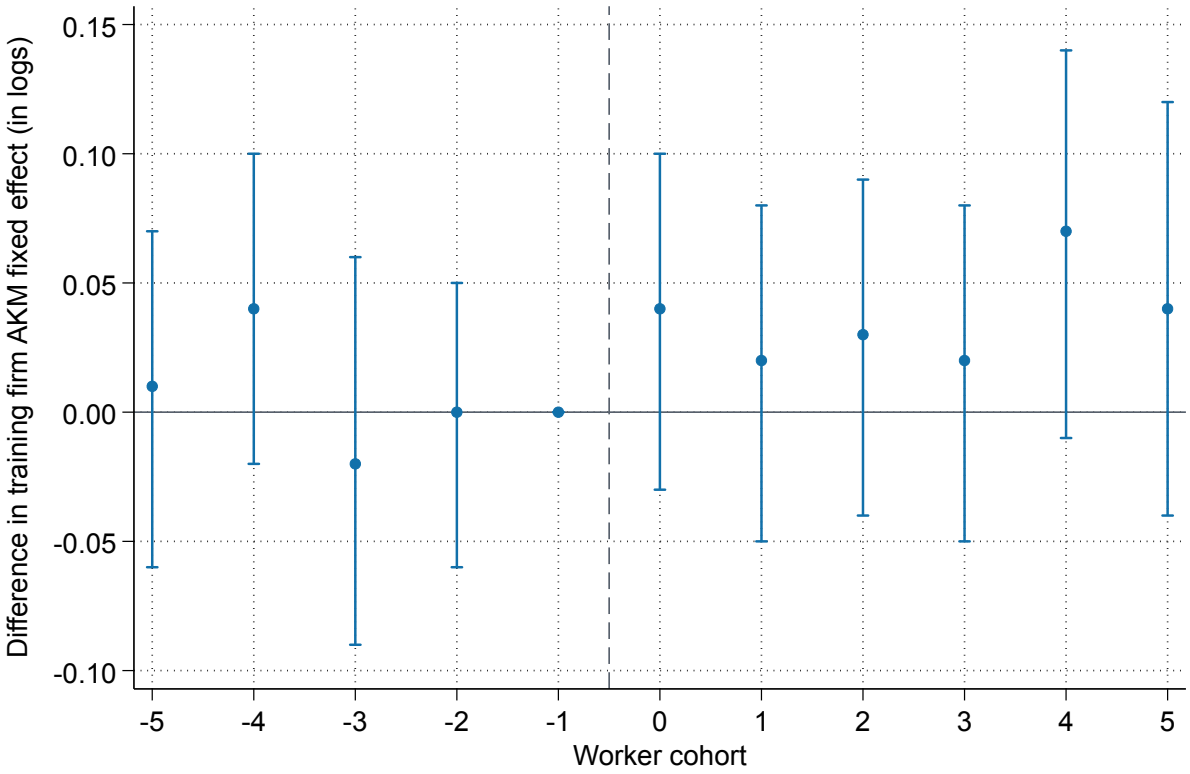


Figure reports stacked difference-in-differences estimates of equation (2), and 95% confidence intervals; estimated separately by year post training. Cohort 0 is the first cohort with the new curriculum; cohort -1 is the reference category. Standard errors clustered at the level of occupation by event. Based on 357 events, $N = 2,193,797$.

updates (See Appendix D in Salomons et al., 2025). Exam pass rates are also unchanged, as is programme selectivity proxied by the share of unfilled apprenticeship positions or unsuccessful apprenticeship applications, indicating that curriculum updates do not alter the pool of workers who complete training. Training firm quality, measured by AKM fixed effects, is also unaffected by curriculum updates, ruling out that wage returns are driven by workers having been trained in higher-paying firms (Figure 3). Results are robust to excluding from the control group those occupations with the highest worker mobility from the treated occupations or those within the same two-digit occupation, mitigating concerns about SUTVA violations (Figure A1). Wage effects are not driven by subsequent educational upgrading by new-skilled workers, as these workers are no more likely to obtain a university or Fachhochschule degree (akin to a university of applied sciences degree) nor a Master craftsman degree within five years of graduation (Figure A2, Panel A). Results are also robust to con-

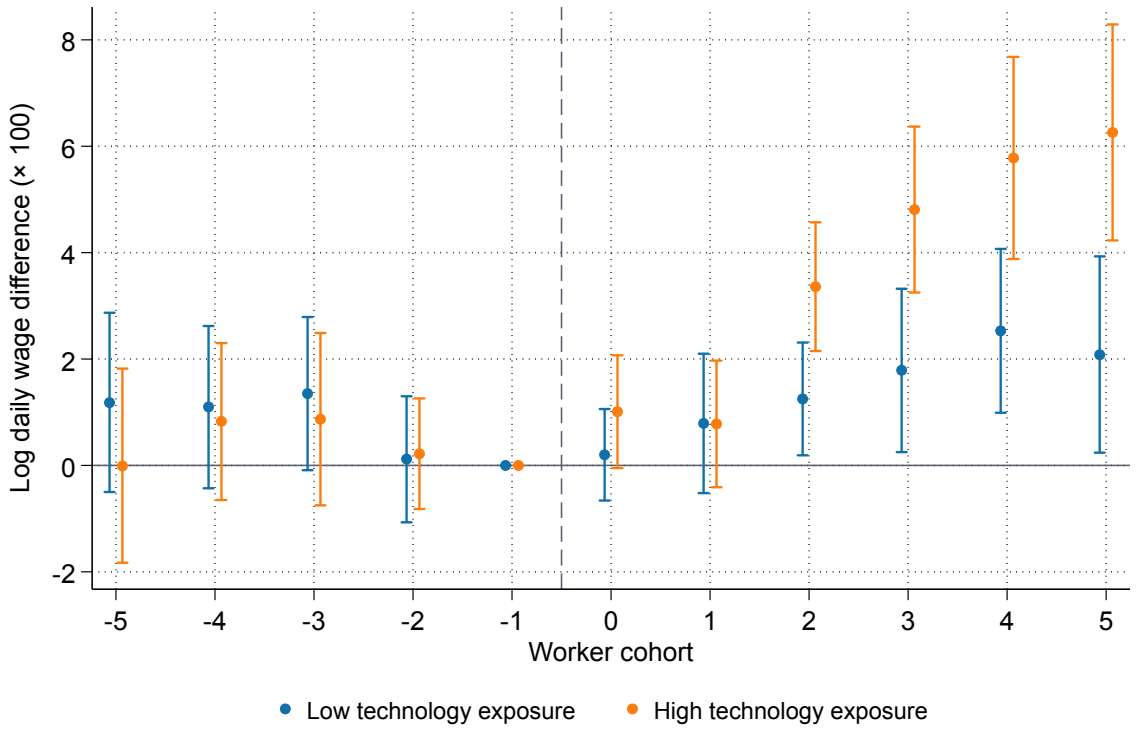
trolling for workers' high school type (Figure A2, Panel B) and hold at each experience level when the model is estimated separately by workers' potential work experience, with wage returns tending to grow with post-training experience as expected (Figure A3 and A4).

3.2.2 The Role of Technology Exposure

To understand the mechanisms underlying improved wage outcomes for workers with updated skills, the analysis examines how wage impacts vary with updated occupations' pre-update technology exposure. Technology exposure is one important driver of curriculum updates, as established above, but curriculum updates occur for various reasons: some involve substantive skill content changes linked to factors plausibly related to technology, such as technological change itself, shifting competence requirements, and firm-level structural change, while others are more procedural, such as changes to examination format, legal regulations, or occupational delimitations. Curricula updated in response to technological advances should generate larger wage returns, since these updates align training content with evolving skill demands and may induce complementary capital investments, whereas other updates are less likely to do so. Figure 4 reports wage returns to curriculum updates separately by high and low technology exposure, defined as whether the treated occupation's exposure to patents exceeds the median exposure. The figure reveals that curriculum updates for highly technology-exposed occupations yield substantially larger wage premia than those for less exposed occupations, with the gap widening for later cohorts. While no difference between high- and low-exposure updates is visible for the first two new-skilled cohorts, cohorts trained in highly technology-exposed occupations two to five years after the curriculum update earn 3.4 percent (cohort 2), 4.8 percent (cohort 3), 5.8 percent (cohort 4), and 6.3 percent (cohort 5) higher wages over the first five years of their careers than the last cohort trained in the old curriculum (c = -1). Corresponding estimates for workers trained in low technology-exposed occupations reach at most 2.5 percent (cohort 4) and stabilise at 2.1 percent for the final cohort. These differences are statistically significant: a Wald test of treatment effect equality between low- and high-exposure updates across all cohorts rejects with $p = 0.00$, and t-tests of equality for individual cohorts reject with $p \leq 0.01$ for cohorts 2 through 5.

These daily wage effects translate to higher annual earnings, with substantially larger effects for more technology-exposed occupations (Figure A5). A potential concern is that observed wage returns are partially driven by ongoing technological change, capturing a demand shift rather than skill-supply effects from discrete curriculum updates. This concern is

Figure 4: Entrant Wage Impacts of Curriculum Updates by Technology Exposure



Stacked difference-in-differences estimates of equation (2), and 95% confidence intervals. Cohort 0 is the first cohort with the new curriculum; cohort -1 is the reference category. Individuals are included up to five years after graduation. Standard errors clustered at the level of occupation by event. $N = 4,715,806$ for low exposure (175 events), and $N = 4,253,227$ for high exposure (182 events). A Wald test of the joint significance of the coefficients for cohorts < -1 yields $p = 0.22$ for low exposure and $p = 0.49$ for high exposure. T-tests of equality of treatment effects between high- and low-exposure updates do not reject for cohorts 0 and 1, and reject with $p \leq 0.01$ for cohorts 2 through 5. A Wald test of treatment effect equality between high- and low-exposure updates across all cohorts rejects with $p = 0.00$.

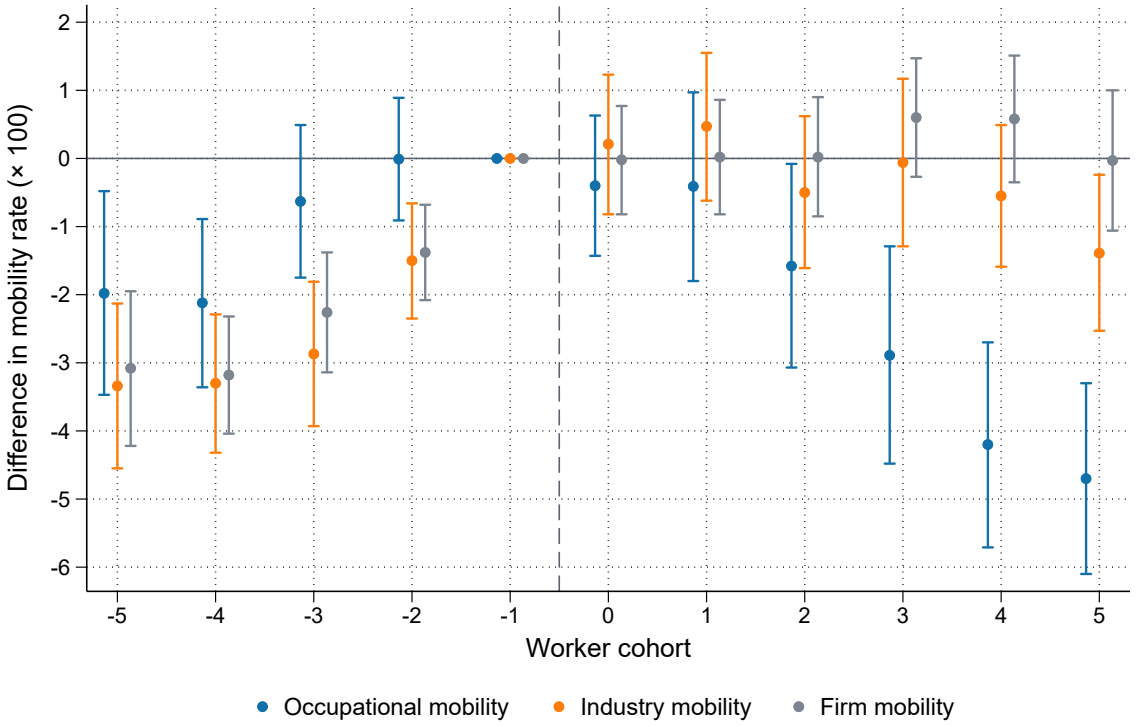
addressed by controlling for each occupation's technology exposure over time, computed by linking the pre-update curriculum text to the patent flow relevant for each cohort, thereby holding constant the technology-driven demand shifts an occupation would have experienced absent a curriculum change. The results are unaffected by this control, demonstrating that the wage returns reflect genuine skill-supply effects from curriculum updates rather than confounding demand shifts (Figure A6). This evidence suggests that technology is a key mechanism underlying wage returns from skill updates: updates spurred by advancing technology impart larger and longer-lasting labour-market advantages than those driven by other factors. This pattern is consistent with the expertise mechanism proposed by Autor et al. (2026), who show that new work within occupations—particularly technology-linked new work—commands wage premia because the specialised expertise it requires is initially scarce. The results add causal evidence to this account, showing that curriculum adaptation produces this novel expertise and raises the wages of workers trained in it.

3.2.3 Occupational Mobility and Retention

The analysis next examines whether the labour-market advantages of curriculum updates accrue from differences in workers' early career paths, using occupation, industry, and firm mobility as outcomes. Figure 5 displays mobility estimates relative to the worker's apprenticeship position, considering whether the worker has moved out of the 4-digit occupation, the 3-digit industry, or the firm where they did their apprenticeship. The mobility estimates reveal a distinct pattern. In the pre-update period, workers in updating occupations are increasingly more likely to leave their training occupation, industry, and firm than comparable workers in non-updating occupations, consistent with workers trained in outdated curricula leaving jobs where their skills are a poor match. Following the curriculum update, firm and industry mobility stabilise, while occupational mobility declines persistently. New-skilled cohorts are up to 4.7 percentage points less likely to leave their training occupation over the first five years of their career, a meaningful reduction relative to the baseline occupational mobility rate of 37 percent. This decrease in occupational mobility aligns with the timing of wage returns, becoming stronger for later cohorts.

The occupational retention finding points to one possible mechanism through which curriculum updates raise wages. Recent research shows that occupational mismatch causes an average wage penalty of 14 percent for German vocationally trained workers, reflecting the non-transferability of occupation-specific human capital across fields (Eckardt, 2026). By better aligning skill supply with current occupational demands, curriculum updates re-

Figure 5: Impacts of Curriculum Updates on Entrant Mobility



Stacked difference-in-differences estimates of equation (2), and 95% confidence intervals. Mobility is defined relative to the apprenticeship position. Cohort 0 is the first cohort with the new curriculum; cohort -1 is the reference category. Individuals are included up to five years after graduation. Standard errors clustered at the level of occupation by event. 357 events, $N = 9,012,391$.

duce the share of workers ending up outside their training field—workers whose training better matches their occupation's skill requirements have less reason to leave. A back-of-the-envelope calculation suggests this channel accounts for less than one-fifth of the observed wage return: combining the 4.7 percentage point reduction in occupational mobility with Eckardt's estimated 14 percent wage penalty for occupational mismatch yields an implied wage gain of 0.7 log points, compared to the 4.1 percent estimated wage return. This calculation indicates that while improved occupational matching contributes to the wage gains, the majority of the return operates through other channels, such as increased productivity from updated skills or complementary capital investments.

3.3 The Role of Skill Mismatch

A central question for understanding the heterogeneity of returns to curriculum updates is whether their wage and mobility effects are larger when the pre-update mismatch between vocational training and current occupational skill requirements is greater. Conceptually, curriculum updates should be particularly valuable where the content of the old curriculum has become poorly aligned with the skills required in the labour market. In such cases, an update can replace obsolete or insufficiently relevant training content with competencies that better match current work tasks. By contrast, an update to a curriculum that remains broadly aligned with occupational demand may involve more marginal adjustments and need not generate equally large returns.

This question is closely related to the role of technological change analysed above. New technologies can make existing skills obsolete, alter task requirements, and generate demand for new competencies. The larger wage returns to curriculum updates in technology-exposed occupations are therefore consistent with the possibility that technological exposure matters partly because it creates larger curriculum–demand gaps. However, technology exposure and mismatch need not coincide perfectly. Curricula may be updated in response to non-technological changes in work organisation, regulation, or occupational boundaries, while some technology-exposed occupations may remain well matched to demand because their curricula have been revised frequently or because technological changes complement rather than displace existing skills. Direct evidence on mismatch is therefore needed to assess whether the returns to updating depend on the extent to which the previous curriculum had become obsolete.

The analysis builds on the Qualification and Career Surveys described in Section 2.4. These surveys provide workers' self-reported assessments of how useful their vocational train-

ing is for their current work. We use the inverse of this measure as an indicator of mismatch between training content and job requirements. As shown above, workers trained under older curricula report lower training usefulness, providing direct evidence that curriculum staleness is associated with a weaker match between training and subsequent work tasks. To characterise the mismatch prevailing before each curriculum update, we construct two measures. Our preferred measure varies by two-digit occupation and year, thereby capturing changes in the degree of mismatch over time. We also report results using a time-constant measure constructed at the more detailed three-digit occupational level. The latter has greater occupational detail but cannot distinguish persistent differences in average mismatch across occupations from changes in mismatch immediately preceding a particular update event.

3.3.1 Wage Effects by Prior Mismatch

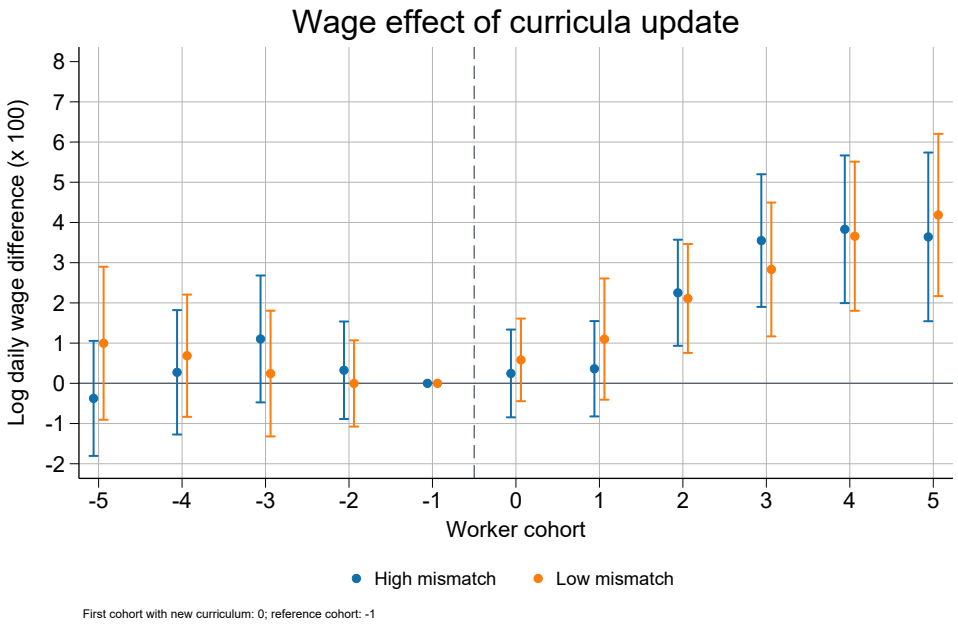
Figure 6 reports wage effects of curriculum updates separately for events with above- and below-median pre-update mismatch. Panel A uses the preferred time-varying mismatch measure at the two-digit occupation-by-year level. The results do not show a clear pattern in which higher mismatch systematically produces larger wage returns to updating. Wage gains emerge after curriculum updates in both high- and low-mismatch settings, and the estimates do not indicate a consistently stronger or more persistent effect for updates undertaken in occupations with greater pre-existing mismatch.

While this finding might suggest that prior mismatch does not matter for the wage returns to curriculum updates, the relationship may be hidden by measurement error or technological change. First, we observe mismatch only at the 2-digit level and only via a survey. The level of aggregation, sample size, and measurement error introduced via the survey could hide the role of prior mismatch for the wage returns of curriculum updates. Moreover, workers' reported training usefulness reflects the match between training and realised jobs, which may itself be affected by occupational sorting, mobility, and local labour-market conditions. Second, correlation between technological change and mismatch could hide differences in wage returns to curriculum updates when splitting the sample solely by mismatch. This is why we next first study mismatch at the 3-digit occupation level (without time variation in mismatch) before turning to the combined roles of mismatch and technological change thereafter.

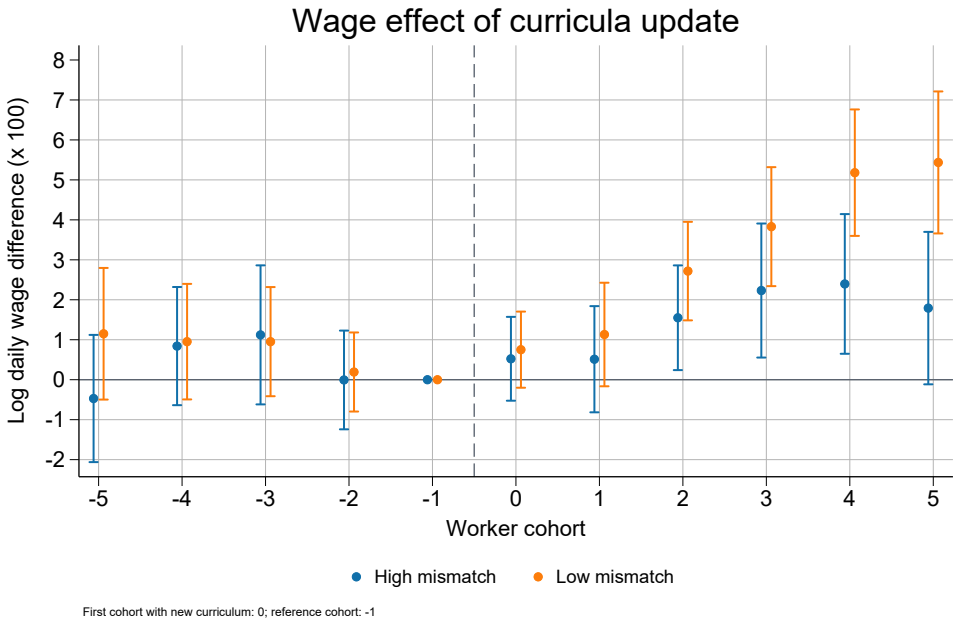
Panel B of Figure 6 uses the time-constant three-digit mismatch indicator and suggests larger wage returns in low-mismatch occupations. We do not interpret this difference as evidence that updates are intrinsically more valuable where mismatch is low. Because this

Figure 6: Impacts of Curriculum Updates on Entrant Wages by Mismatch

A. Mismatch at 2-digit occupations times years



B. Mismatch at 3-digit occupations (time contant)



Stacked difference-in-differences estimates, and 95% confidence intervals. Cohort 0 is the first cohort with the new curriculum; cohort -1 is the reference category. Individuals are included up to five years after graduation. Standard errors clustered at the level of occupation by event.

measure does not vary over time, it primarily captures persistent cross-occupational differences in average mismatch. Occupations classified as low mismatch may differ systematically from high-mismatch occupations in unobserved ways, including their labour-market prospects, training quality, occupational specificity, employer composition, or propensity to update curricula in response to changing demand. The resulting comparison is therefore likely to reflect selection across occupations rather than the causal role of mismatch immediately before an update. For this reason, the time-varying results in 6, Panel A provide the more informative evidence for the present question.

3.3.2 Mismatch and Technology Exposure

Prior mismatch alone does not generate a simple ranking of wage returns. However, the relationship may be hidden if mismatch correlates with technology exposure. Indeed, Figure 7 shows that mismatch and technology exposure jointly shape the value of curriculum updating. The figure separates update events by both pre-update mismatch and technology exposure, using the time-varying two-digit occupation-by-year mismatch measure.

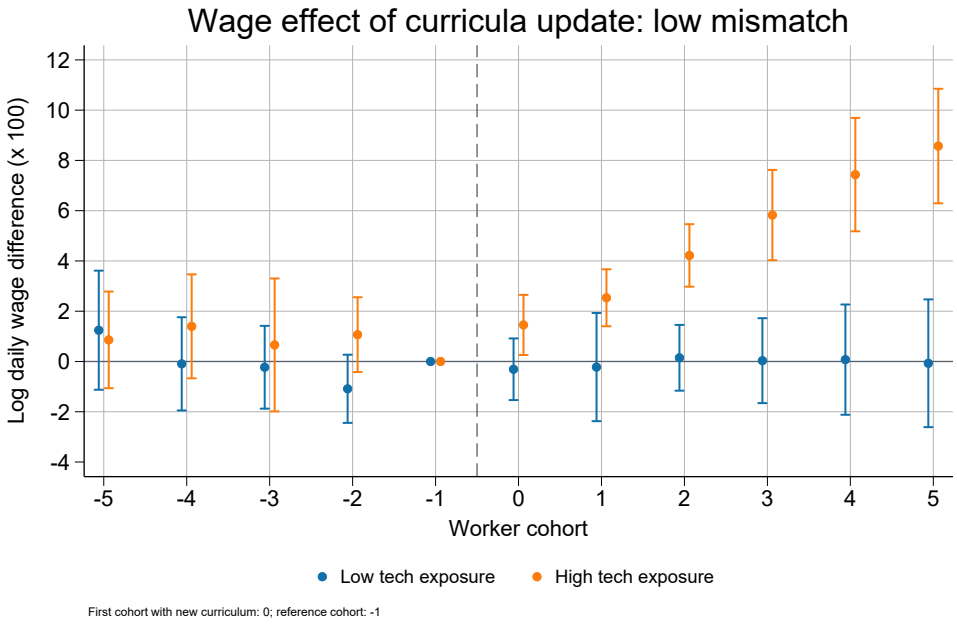
Among low-mismatch occupations, wage returns to curriculum updates are concentrated in technology-exposed occupations. Updates in low-mismatch and low-technology-exposure occupations produce little evidence of sustained wage gains. This pattern is economically intuitive. If an occupation displays neither a substantial observable mismatch between training and work nor strong exposure to new technologies, there may be limited scope for a curriculum revision to alter the skills that are scarce or valuable in the labour market. In contrast, even where the available mismatch measure indicates relatively good alignment between existing training and current work, technology exposure may create demand for new competencies that are not fully reflected in self-reported training usefulness. Updating curricula in these occupations can therefore still generate sizeable wage gains.

The pattern differs among high-mismatch occupations. In these occupations, curriculum updates are associated with positive wage returns under both low and high technology exposure. This result suggests that when the mismatch between training and work requirements is already substantial, an update can be valuable even in the absence of strong measured technology exposure. Changes in occupational demand that create mismatch may arise from sources other than the technological breakthroughs captured by the patent-based measure, including changes in workplace organisation, regulation, production processes, customer requirements, or the relative importance of particular tasks and competencies.

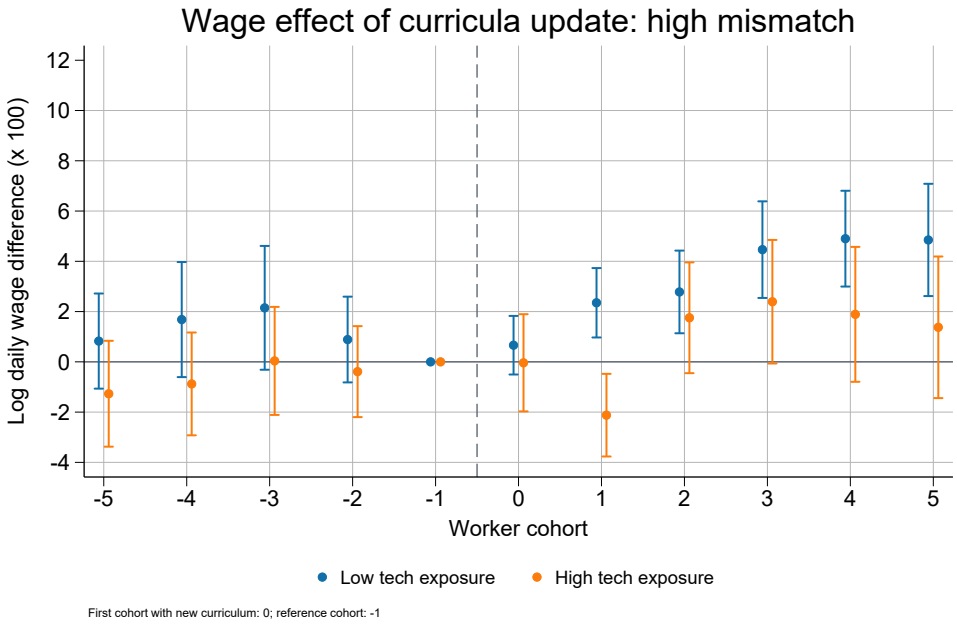
At the same time, the high-mismatch and high-technology-exposure estimates are smaller

Figure 7: Impacts of Curriculum Updates on Entrant Wages by Mismatch and Technology Exposure (2-digits occupations times years)

A. Low Mismatch



B. High Mismatch



Stacked difference-in-differences estimates, and 95% confidence intervals. Cohort 0 is the first cohort with the new curriculum; cohort -1 is the reference category. Individuals are included up to five years after graduation. Standard errors clustered at the level of occupation by event.

and less precisely estimated than the corresponding estimates for some other groups. This pattern should be interpreted cautiously. One possible explanation is that occupations facing both high mismatch and rapid technological change experience especially difficult adjustment problems: the curriculum update may improve the skills of new entrants, but it may not fully offset the pace or breadth of changing task requirements. However, the estimates do not provide conclusive evidence for this interpretation. The more conservative conclusion is that wage gains from curriculum updates are not confined to a single combination of mismatch and technology exposure, but that the source of those gains differs across settings. Technology exposure appears particularly important when observed mismatch is low, whereas substantial mismatch itself is associated with returns to updating even when measured technology exposure is limited.

Appendix Figure A7 reports the same joint analysis using the time-constant three-digit mismatch measure. As with Figure 6, these results should be read primarily as descriptive comparisons across occupations. Because the measure captures persistent occupational characteristics rather than time-varying mismatch before a specific reform, it is difficult to separate the role of mismatch from broader differences in occupational composition and labour-market opportunities.

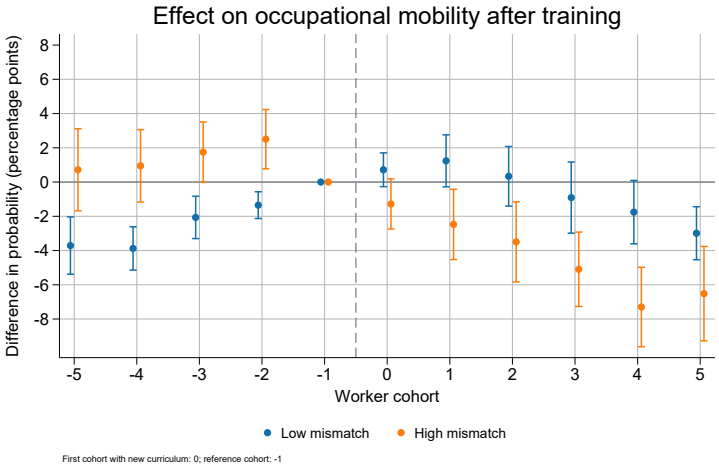
3.3.3 Mobility Effects by Prior Mismatch

Mismatch has a clearer role in the analysis of occupational mobility. Figure 8 reports the effect of curriculum updates on mobility relative to the apprenticeship occupation, industry, and firm separately for high- and low-mismatch update events. Panel A shows that workers in occupations approaching a curriculum update become increasingly likely to leave their training occupation already before the reform. The pattern is consistent with the interpretation that, as the content of the existing curriculum becomes less well aligned with occupational requirements, newly trained workers are more likely to leave the occupation in which they were trained.

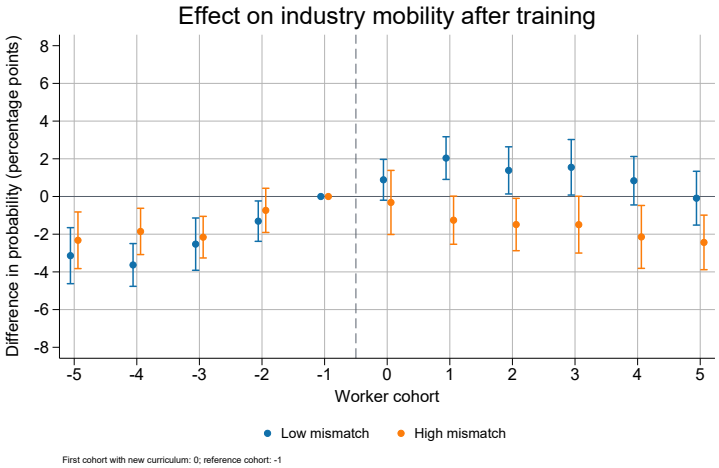
The presence of pre-trends means that these estimates should not be interpreted as a conventional event study with flat pre-treatment coefficients. Rather, the changing mobility patterns are themselves informative about the dynamics surrounding curriculum revision. Curriculum updates do not arrive randomly in time: they are often initiated when employers, social partners, or policymakers perceive that existing training regulations no longer adequately reflect changing occupational requirements. Rising occupational mobility before an update is consistent with this institutional process, as it may reveal a growing difficulty

Figure 8: Impacts of Curriculum Updates on Entrant Mobility by Mismatch (2-digits occupations times years)

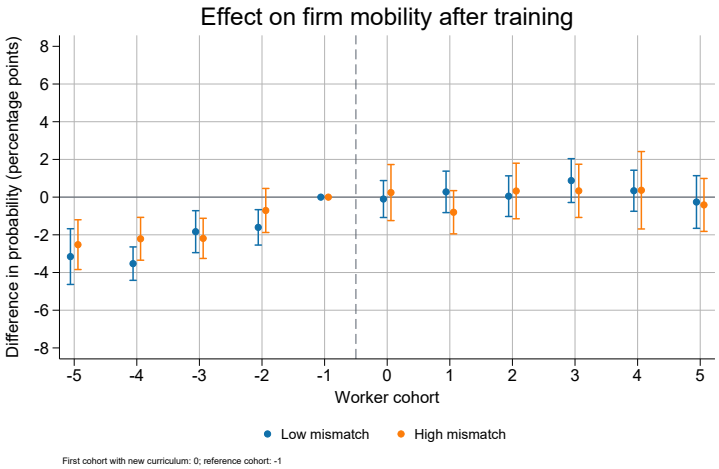
A. Occupational Mobility



B. Industry Mobility



C. Firm Mobility



Stacked difference-in-differences estimates, and 95% confidence intervals. Cohort 0 is the first cohort with the new curriculum; cohort -1 is the reference category. Individuals are included up to five years after graduation. Standard errors clustered at the level of occupation by event.

in retaining newly trained workers in the occupation for which they completed their apprenticeship.

Following an update, this upward pre-trend in occupational mobility is interrupted. In low-mismatch occupations, mobility returns towards its earlier level, suggesting that the new curriculum stabilises occupational attachment after the period of rising exits preceding the revision. In high-mismatch occupations, the post-update decline in occupational mobility appears larger and more persistent. New-skilled workers are substantially less likely to leave their training occupation than cohorts trained shortly before the update. This pattern is consistent with curriculum revisions restoring the relevance of vocational training in occupations where the gap between the old curriculum and work requirements had become particularly pronounced.

The occupational-mobility findings thus provide more direct support for the mismatch mechanism than the wage results alone. Whereas wage returns reflect several channels – including skill productivity, employer demand for new expertise, complementary capital investments, and occupational sorting—the decision to remain in one's training occupation is closely related to whether acquired skills remain usable in that occupation. The larger post-update reduction in occupational mobility in high-mismatch cases is therefore consistent with the interpretation that curriculum updates reduce skill obsolescence and improve the match between vocational preparation and early-career work.

Panels B and C of Figure 8 show the corresponding results for industry and firm mobility. These outcomes exhibit modest pre-update increases, indicating that workers in occupations approaching a curriculum update also become somewhat more likely to leave their industry or apprenticeship firm. As for occupational mobility, the update interrupts these trends, consistent with improved matching between newly trained workers and the jobs available in their original labour-market segment. However, the differences between high- and low-mismatch occupations are substantially less pronounced for industry and firm mobility than for occupational mobility. This distinction is informative: curriculum updates appear to affect the occupational relevance of training most directly, while their effects on the choice of employer or industry are weaker and likely mediated by other features of local labour markets and career opportunities.

Appendix Figure A8 replicates the mobility analysis using the time-constant three-digit mismatch measure. These estimates again reflect persistent differences across occupations as well as mismatch, and should therefore not be given the same causal interpretation as the time-varying analysis in Figure A10.

Taken together, the results suggest that curriculum updating is most clearly associated with improved occupational retention where prior mismatch is high, while wage gains do not rise monotonically with the available mismatch measure. This combination of findings is substantively plausible. Updates can reduce the need for workers to leave their training occupation when the old curriculum has become poorly aligned with occupational requirements, but the wage value of newly introduced skills also depends on whether those skills are linked to technological change, emerging tasks, or other sources of employer demand. Curriculum revisions therefore appear to operate through both a mismatch-reduction channel—improving the fit between workers' training and their occupation—and an expertise-creation channel, whereby updates provide competencies that command wage premia in changing labour markets.

4 Conclusions

This report documents the scientific progress achieved under Task 5.4 of the SkiLMeeT project, which examines how skill mismatches between vocational training and labour-market demand shape workers' careers and how curriculum updates can mitigate these mismatches. The analysis combines the near-universe of legally binding German vocational training curricula from 1971 to 2021 with patent-based measures of technological change, administrative employer–employee records, and survey-based indicators of training usefulness. This setting makes it possible to identify the effects of discrete, nationally standardised curriculum revisions on the early-career outcomes of vocationally trained workers.

The results show that curriculum updates generate economically meaningful benefits for labour-market entrants. Workers trained under an updated curriculum earn up to 4.1 percent higher daily wages than comparable workers trained under the preceding curriculum vintage, and the annual-earnings results indicate that these gains arise predominantly through wages rather than changes in employment attachment. The wage effects are not explained by changes in trainee composition, training-firm quality, subsequent educational upgrading, or alternative definitions of the comparison group. They instead indicate that curriculum updates provide skills that are valued by employers and improve workers' productivity in the occupations for which they train.

Technology exposure is an important dimension of this pattern. Wage returns to updated curricula are substantially larger and more persistent in occupations with high exposure to digital technological breakthroughs. For cohorts trained several years after an update, wage

gains in highly exposed occupations reach more than 6 percent, compared with considerably smaller effects in low-exposure occupations. These findings remain when controlling for technology-driven changes in occupational demand associated with the old curriculum. They therefore point to a skill-supply effect of curriculum adaptation, rather than merely reflecting stronger demand growth in technologically changing occupations. Curriculum updates appear to help vocational training keep pace with the emergence of new tasks and expertise requirements created by technological progress.

The findings also show that curriculum revisions affect workers' early career mobility. New-skilled cohorts are less likely to leave the occupation in which they completed their apprenticeship, with occupational mobility declining by up to 4.7 percentage points relative to workers trained under the old curriculum. This reduction is sizeable given that 37 percent of entrants leave their training occupation during the first five years after graduation. The effects on industry and firm mobility are weaker, suggesting that curriculum updates primarily improve the match between workers' acquired skills and their trained occupation, rather than simply binding workers more strongly to a particular employer or sector.

The mismatch analysis clarifies this mechanism. Using workers' reported usefulness of vocational training as an inverse measure of mismatch, we find that occupations approaching a curriculum update display rising occupational mobility before the revision, especially when pre-update mismatch is high. This pattern is consistent with workers leaving occupations in which their training has become less relevant to current work requirements. Following an update, the increase in occupational mobility is interrupted. The decline in occupational exits is particularly strong in high-mismatch occupations, indicating that revised curricula can restore the occupational relevance of vocational training where the gap between old training content and labour-market requirements has become most pronounced.

The evidence on wages is more nuanced. Higher prior mismatch does not mechanically imply larger wage returns to updating. Instead, wage gains reflect the joint role of mismatch and technology exposure. In occupations with relatively low measured mismatch, curriculum updates generate substantial wage returns principally where those occupations are exposed to new technologies. Where mismatch is already high, updates are associated with wage gains under both low and high technology exposure. This pattern suggests that curriculum reform can respond to several sources of changing skill demand. Technological change is especially important for generating valuable new expertise in occupations where existing training remains broadly relevant, while pronounced mismatch can make curriculum renewal valuable even where the available patent-based measure captures less technological change.

Taken together, the results identify curriculum revision as a policy lever for addressing technologically induced skill obsolescence and improving the match between vocational training and work. The German dual system's institutionalised process for revising nationally standardised curricula provides a mechanism through which training content can be updated in response to changing occupational requirements. However, the findings also imply that maintaining relevance requires more than occasional reform. Occupations with rapid technological change face a continuing need to update curricula, while occupations with high mismatch benefit from revisions that restore the connection between acquired skills and actual work tasks.

Several implications follow for vocational-education policy. First, systematic information on occupational skill demand and curriculum–demand mismatch can help identify curricula for which revision is most urgent. Second, technology exposure is a useful complementary early-warning indicator: even where observed mismatch remains limited, technology-exposed occupations may benefit substantially from proactive updates that prepare entrants for emerging tasks. Third, policy evaluation should consider not only wages but also occupational retention and mobility. A curriculum can create value by allowing workers to remain productively employed in their trained occupation, thereby preserving occupation-specific human capital and reducing costly career adjustments. Finally, the results underline the importance of regularly updating detailed, occupation-specific training content in systems that rely heavily on vocational education. Such updates can support both workers' career prospects and firms' ability to adopt and use new technologies.

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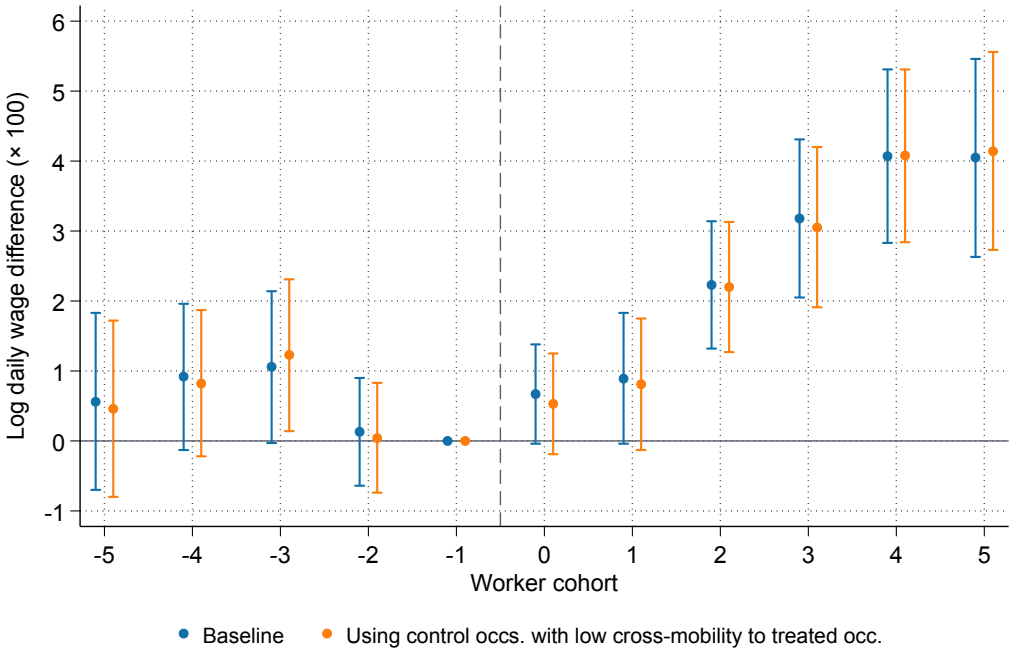
A Additional Figures and Tables

Figure A1: Impact of Curriculum Updates on Entrant Wages: Control Group Robustness Checks

A. Only using control occupations with low mobility to and from treated occupations



B. Only using control occupations from different 2-digit occupations than treated occupations

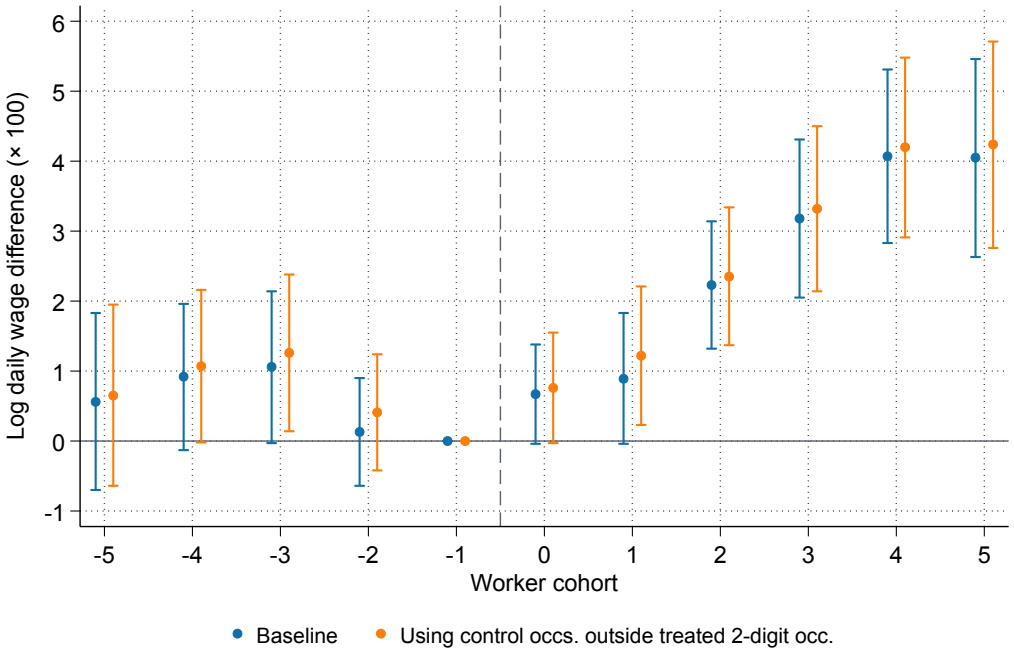
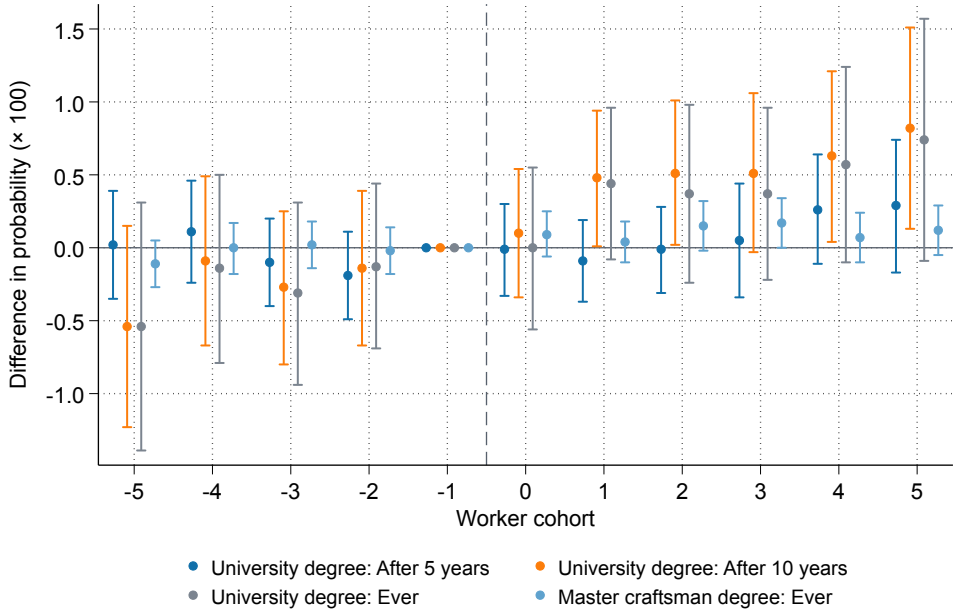


Figure reports stacked difference-in-differences estimates of equation (2), and 95% confidence intervals. Cohort 0 is the first cohort with the new curriculum; cohort -1 is the reference category. Individuals are included up to five years after graduation. Standard errors clustered at the level of occupation by event. Both panels based on 357 events. Panel A: $N = 8,913,473$; Panel B: $N = 5,621,395$.

Figure A2: Impacts of Curriculum Updates for Entrants: Education-Related Robustness Checks

A. Later Educational Upgrading: Obtaining a University or Master Craftsman Degree



B. Daily Wages, Controlling for High School Education Type

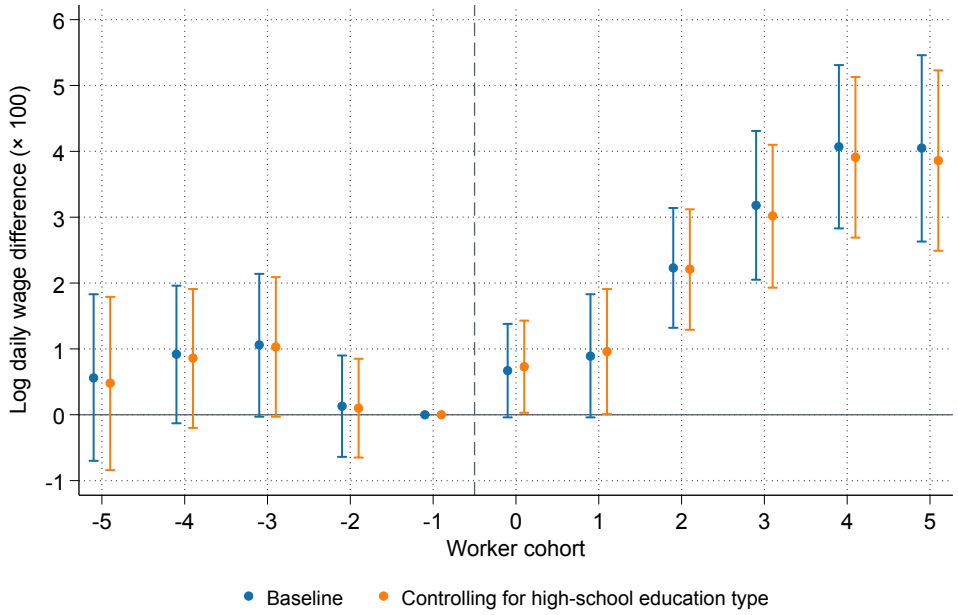


Figure reports stacked difference-in-differences estimates of equation (2), and 95% confidence intervals; estimated separately by year post training. Cohort 0 is the first cohort with the new curriculum; cohort -1 is the reference category. Standard errors clustered at the level of occupation by event. Based on 357 events for both panels; $N = 2,232,166$ for panel A; $N = 8,969,021$ for panel B.

Figure A3: Entrant Log Daily Wage Impacts of Curriculum Updates By Post-Training Year

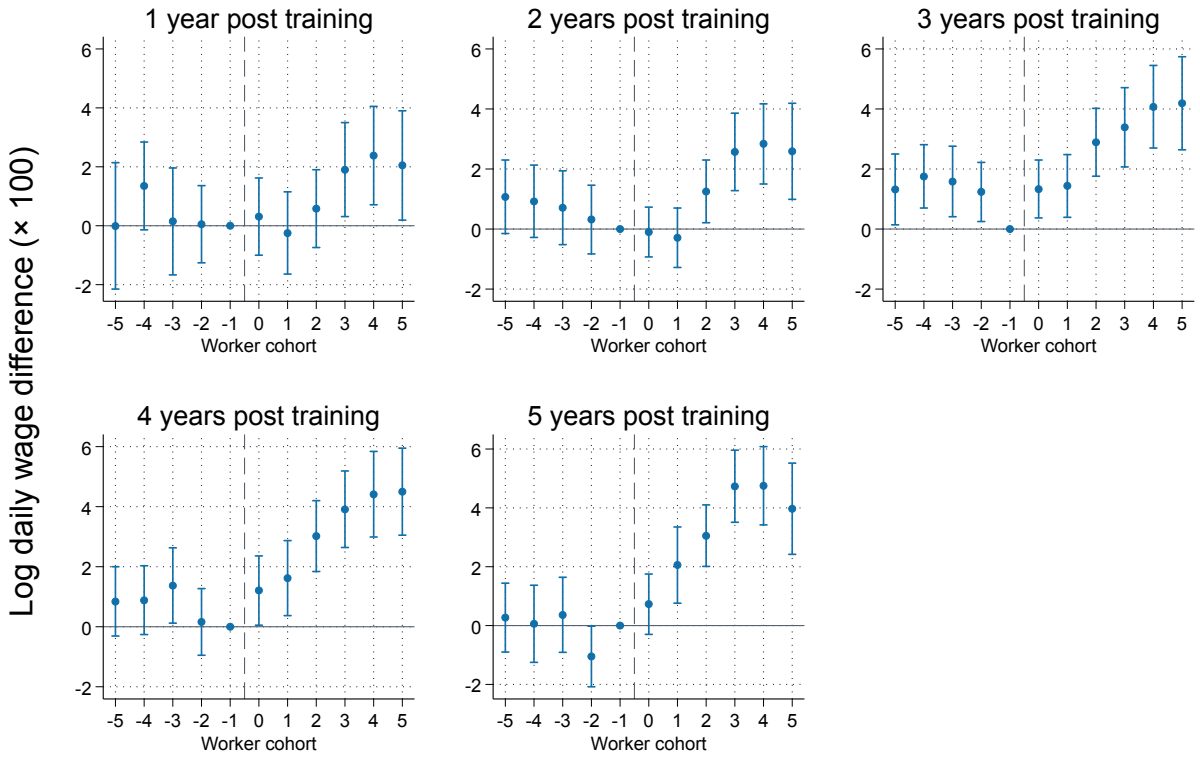


Figure reports stacked difference-in-differences estimates of equation (2), and 95% confidence intervals; estimated separately by year post training. Cohort 0 is the first cohort with the new curriculum; cohort -1 is the reference category. Standard errors clustered at the level of occupation by event. 357 events. Observation numbers by year of post-training: $N_1 = 1,995,317$; $N_2 = 1,818,463$; $N_3 = 1,764,340$; $N_4 = 1,709,493$; $N_5 = 1,661,285$.

Figure A4: Entrant Log Daily Wage Impacts of Curriculum Updates By Post-Training Year and Technology Exposure

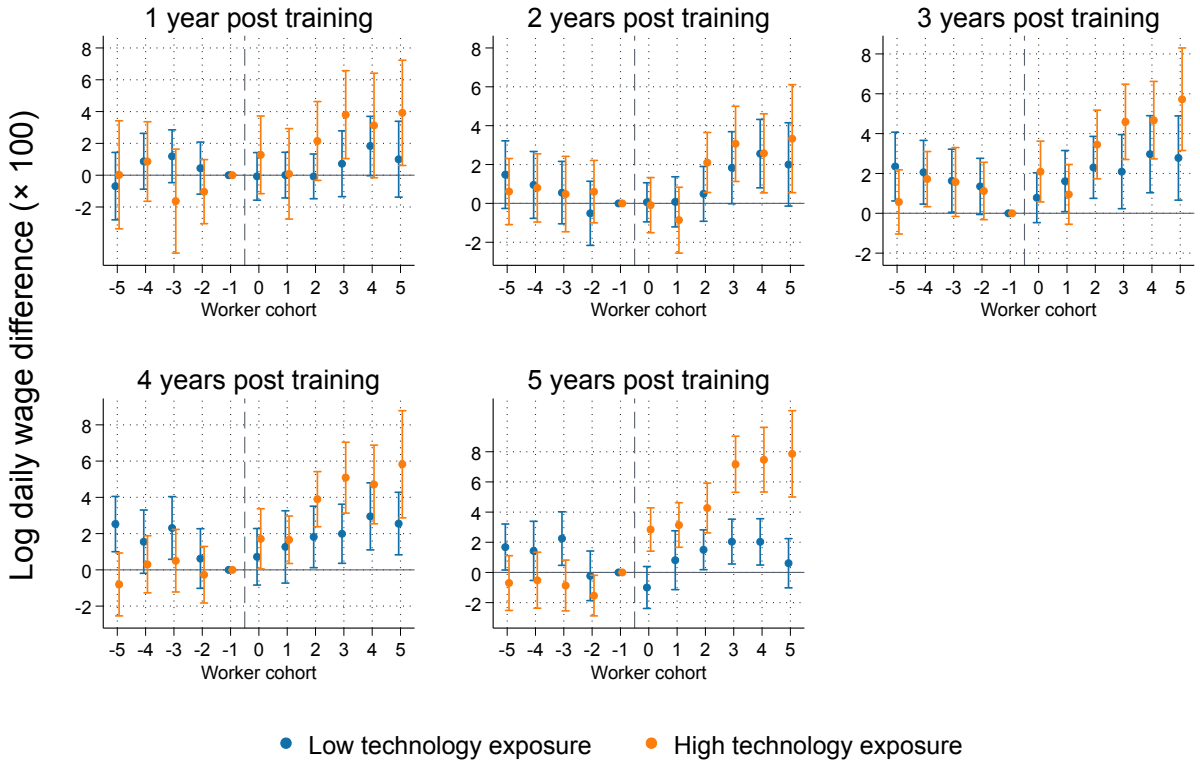


Figure reports stacked difference-in-differences estimates of equation (2), and 95% confidence intervals; estimated separately by year post training. For example, the series labeled '5 years post training' shows how log daily wages in the fifth year after vocational training completion evolve across worker cohorts. Cohort 0 is the first cohort with the new curriculum; cohort -1 is the reference category. Standard errors clustered at the level of occupation by event. 175 events for low exposure, 182 events for high exposure. Observation numbers by year of post-training and technology exposure: $N_1^{\text{high}} = 957,491$; $N_2^{\text{high}} = 869,913$; $N_3^{\text{high}} = 837,195$; $N_4^{\text{high}} = 802,627$; $N_5^{\text{high}} = 774,957$; $N_1^{\text{low}} = 1,037,826$; $N_2^{\text{low}} = 948,550$; $N_3^{\text{low}} = 927,145$; $N_4^{\text{low}} = 906,866$; $N_5^{\text{low}} = 886,328$.

Figure A5: Impact of Curriculum Updates on Entrant Annual Income by Technology Exposure

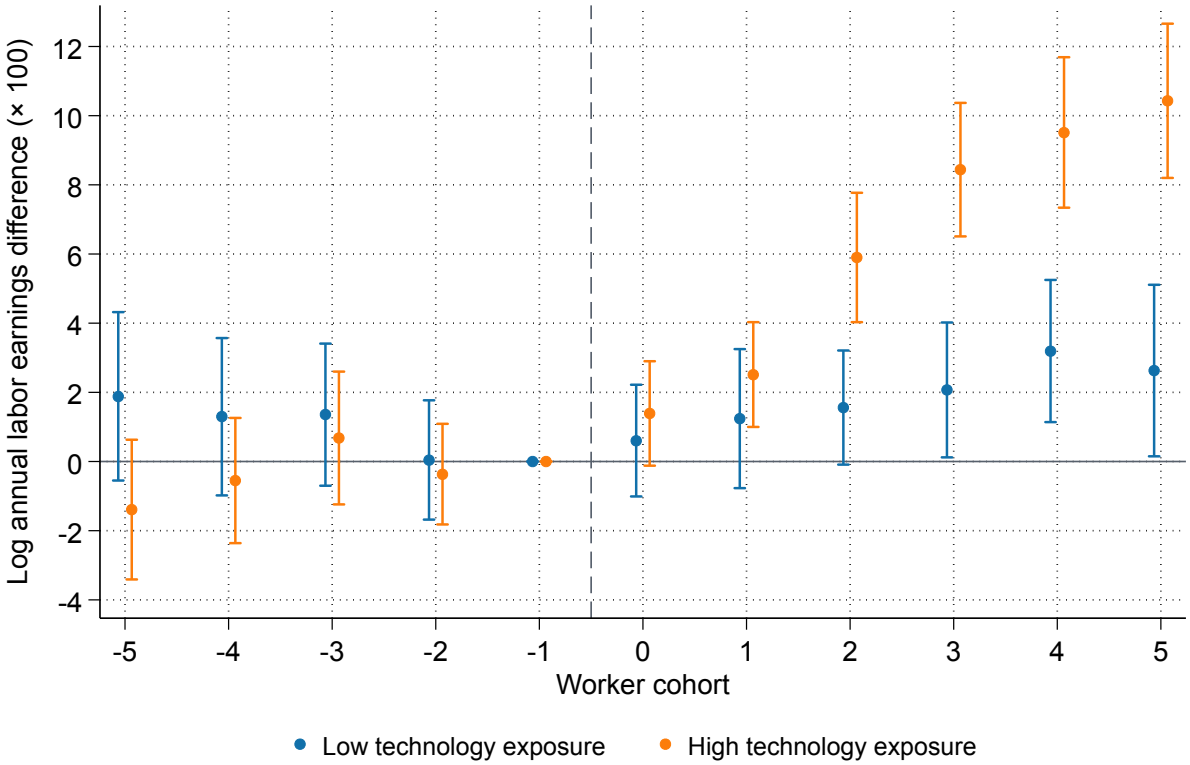
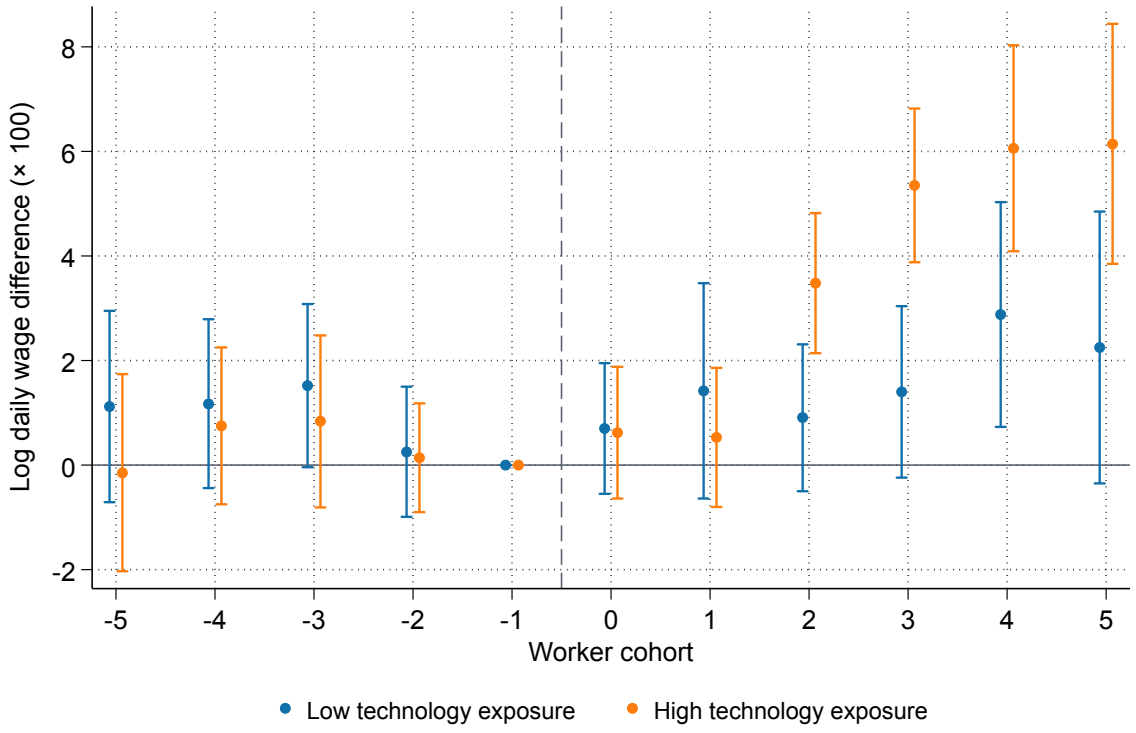


Figure reports stacked difference-in-differences estimates of equation (2), and 95% confidence intervals. Cohort 0 is the first cohort with the new curriculum; cohort -1 is the reference category. Individuals are included up to five years after graduation. Standard errors clustered at the level of occupation by event. $N = 4,253,227$ for high exposure (182 events), and $N = 4,715,806$ for low exposure (175 events).

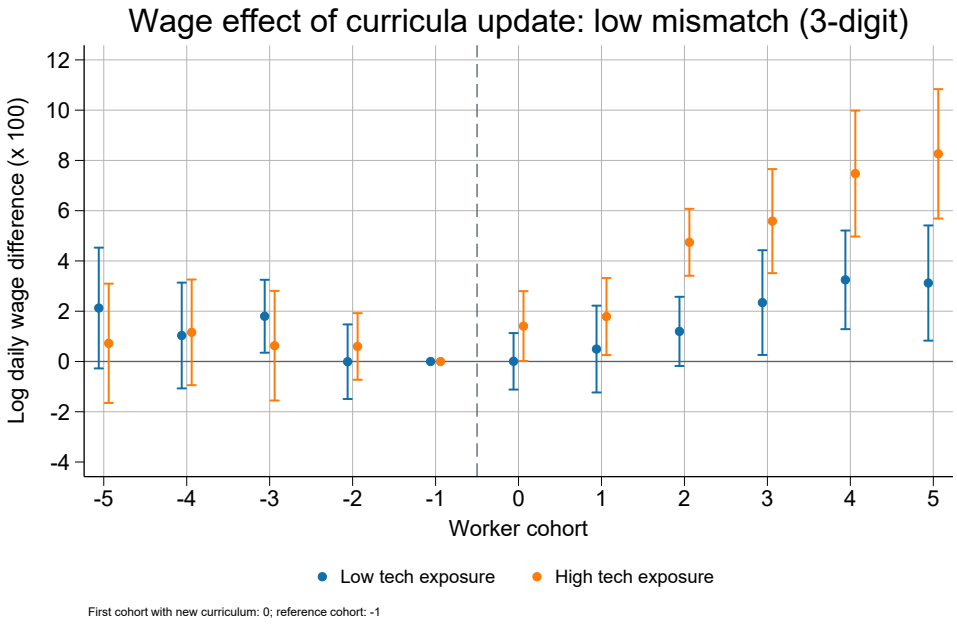
Figure A6: Entrant Wage Impacts of Curriculum Updates by Technology Exposure, Controlling for Prior-Curriculum Technology Exposure



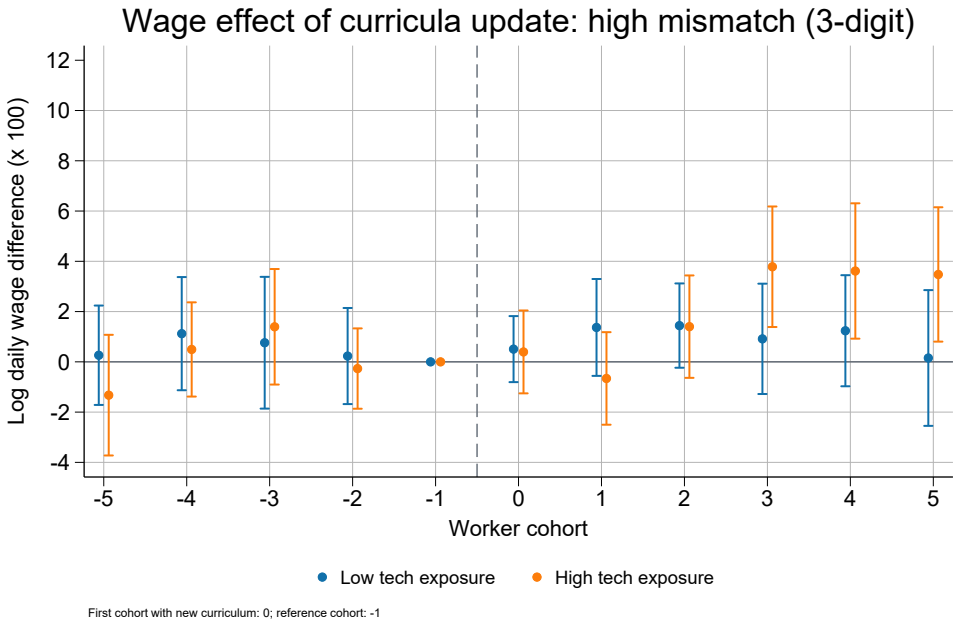
Stacked difference-in-differences estimates of equation (2), and 95% confidence intervals. Cohort 0 is the first cohort with the new curriculum; cohort -1 is the reference category. Individuals are included up to five years after graduation. Standard errors clustered at the level of occupation by event. Technology exposure of the prior curriculum is defined as the log number of (lagged) digital breakthrough patents linked to the occupation's curriculum in $t = -1$. $N = 4,286,088$ for low exposure (175 events), and $N = 4,066,761$ for high exposure (182 events).

Figure A7: Impacts of Curriculum Updates on Entrant Wages by Mismatch and Technology Exposure (3-digit occupations)

A. Low Mismatch



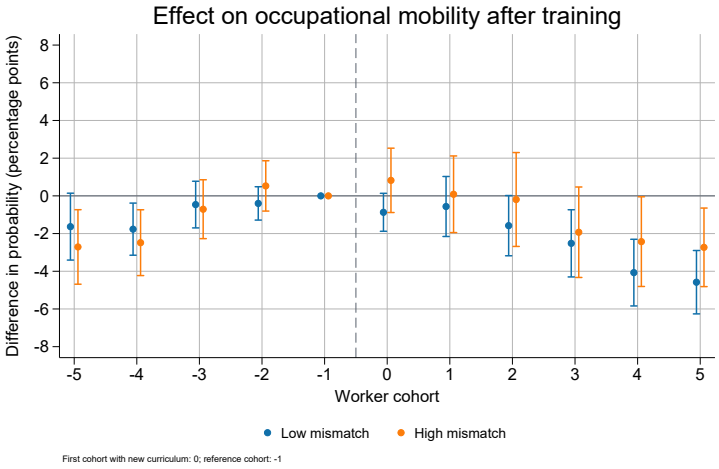
B. High Mismatch



Stacked difference-in-differences estimates, and 95% confidence intervals. Cohort 0 is the first cohort with the new curriculum; cohort -1 is the reference category. Individuals are included up to five years after graduation. Standard errors clustered at the level of occupation by event.

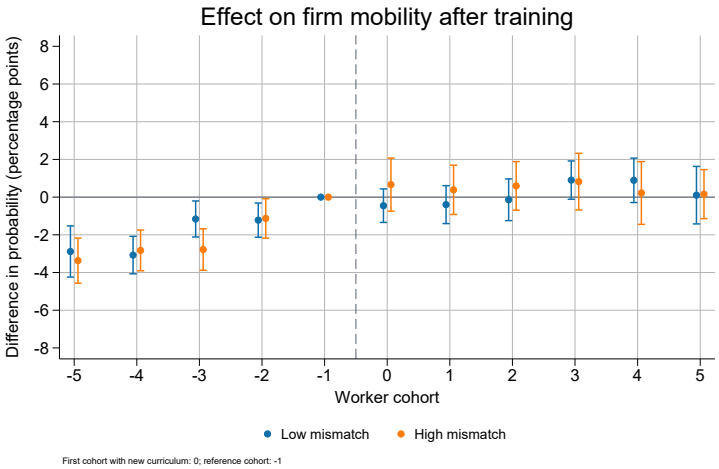
Figure A8: Impacts of Curriculum Updates on Entrant Mobility by Mismatch (3-digit occupations)

A. Occupational Mobility



B. Industry Mobility

C. Firm Mobility



Stacked difference-in-differences estimates, and 95% confidence intervals. Cohort 0 is the first cohort with the new curriculum; cohort -1 is the reference category. Individuals are included up to five years after graduation. Standard errors clustered at the level of occupation by event.

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