The Supply of Expertise: New Technologies, New Skills, and Worker Impacts*

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Abstract

Does educational content respond to technological advances, and do such changes enable workers to acquire new valuable expertise? We construct a novel database of legally binding training curricula spanning the near universe of vocational training in Germany over five decades, and link curriculum updates to breakthrough technologies using Natural Language Processing. We trace a causal chain from technological change to curriculum content to worker outcomes. Technological change spurs curriculum updates, and training content shifts toward less routine-intensive tasks. This shift occurs predominantly through the emergence of new skills related to social, digital, and problem-solving competencies, rather than the removal of old ones. This within-occupation margin is quantitatively important: curriculum updates account for two-thirds of the overall deroutinization in vocational skill supply over this period. Using administrative employer-employee data and a stacked difference-in-differences design, we show that new-skilled workers earn higher wages, especially in technology-exposed occupations, and are more likely to remain employed in their trained occupation. In contrast, older occupational incumbents experience wage declines, indicating skill obsolescence. These findings highlight the central role of within-occupation skill supply adjustments—not just educational attainment—in meeting evolving labor market demands.

Keywords: Technological Change, Skill Updating, Skill Obsolescence, Vocational Training, Educational Content

JEL codes: J23, J24, J31, O33

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1 Introduction

Technological progress reshapes occupational skill requirements over time. Digital technologies automate routine tasks (Autor et al., 2003; Acemoglu and Autor, 2011; Goos et al., 2014; Restrepo, 2024), raise the demand for IT skills and social competencies (Deming, 2017; Cortes et al., 2023; Aghion et al., 2026), and create new work—novel job tasks demanding specialized human knowledge that was not previously used in production (Lin, 2011; Acemoglu and Restrepo, 2018, 2019; Autor et al., 2024). Because the expertise these tasks require is initially scarce, it commands substantial wage premia (Autor et al., 2026). How is this new expertise supplied? The canonical answer emphasizes raising educational attainment (Tinbergen, 1975; Goldin and Katz, 2008), yet technology also transforms *what skills the labor market rewards*, not only how much education workers need. This points to a distinct margin of adjustment: the evolution of educational content *within* programs and occupations. Whether skill supply adjusts along this margin is unknown, yet consequential: within-occupation task changes—not shifts across occupations—account for the majority of aggregate changes in skill demand (Spitz-Oener, 2006; Atalay et al., 2020).

This paper asks whether educational content adapts to technological change, and whether such adaptation reinstates workers' expertise—their capability to perform economically valuable tasks (Autor and Thompson, 2025; Autor et al., 2026). We construct novel data spanning five decades of vocational training curricula in Germany, covering the near-universe of formal non-college occupational training. Linking these data to patent-based measures of technological progress and administrative employer-employee records, we trace a complete causal chain, illustrated in Figure 1. Technological advances drive discrete curriculum updates which introduce newly emerging skill content; this new content reinstates worker expertise, raising wages for those who acquire it; and the resulting new skill supply leads to incumbent skill obsolescence.

Vocational training in Germany—a full-time post-secondary educational program combining classroom instruction with firm-based training—offers an ideal setting to study these questions, for three reasons. First, the 1969 Vocational Training Act mandates that virtually all German vocational training is codified in nationally standardized, legally binding curricula, certified through externally administered final examinations. These curricula are regularly revised through an institutionalized process (described in Section 2). This allows us to observe comprehensive content changes over half a century and to know precisely which skill vintage each worker acquired—which is infeasible in most educational systems, where

training content decisions are uncodified, decentralized, or not externally assessed. Our setting lets us describe how curricula change and identify the causal effects of these changes, as we detail below. Second, this setting covers a substantial share of the labor market: vocationally trained workers constitute 70% of the German workforce over our sample period, more than five times the 12% share with a university degree.[1] Vocational training programs prepare workers for a wide range of jobs in both manufacturing and services, including technical occupations in automotive industries, in machine-building and -operating, and in electrical engineering, as well as administrative, logistics, and retail jobs. Third, these vocationally trained workers are concentrated in middle-wage occupations that have been most exposed to task automation over the past decades (Autor et al., 2006; Goos and Manning, 2007; Acemoglu and Autor, 2011; Goos et al., 2014), precisely where understanding skill-supply adaptation matters most for economic and policy outcomes (Holzer, 2026).

We employ two complementary empirical strategies. First, to identify the causal effect of technological change on curriculum updates and content, we link training curricula to lagged patents using Natural Language Processing, following Seegmiller et al. (2023). For identification, we use breakthrough patents (Kelly et al., 2021), which capture discontinuous shifts in the innovation frontier that are plausibly exogenous to contemporaneous skill supply decisions. Second, to identify the causal effect of curriculum updates on worker outcomes—both the returns to newly acquired expertise and the resulting obsolescence of incumbents' skills—we exploit hundreds of curriculum update events in two stacked difference-in-differences (DiD) designs. To estimate returns to new expertise among labor market entrants, we compare cohorts of old-skilled workers (trained before a curriculum update) and new-skilled workers (trained after) in updating occupations to corresponding cohorts in occupations without updates over the same time window. To estimate incumbent obsolescence, we follow individual occupational incumbent workers over time, comparing their outcomes before and after a curriculum update in their occupation relative to incumbents in occupations without updates. Both DiD designs rest on the discontinuity of curriculum revision: while skill demand shifts evolve gradually (the dashed arrow in Figure 1), curriculum updates arrive at a specific, legally documented date. Discrete changes in outcomes around the update can therefore be attributed to the change in skill supply rather than to ongoing demand trends. Consistent with this, results are robust to controlling for each curriculum's evolving technology exposure.

[1] Averages over 1975–2021, based on the Sample of Integrated Labor Market Biographies (SIAB).

We establish four sets of findings. First, technological advances drive curriculum updates: occupations more exposed to digital technology update their training content more frequently and more rapidly, with a one-standard-deviation increase in technology exposure raising the annual update probability by 33% relative to the average.

Second, these updates reshape training content substantially: curricula shift toward less routine-intensive tasks, predominantly through the emergence of new skills rather than the removal of old ones. New expertise skews toward social, digital, and problem-solving competencies, increasing workers' self-reported usefulness of their skills. This within-occupation adjustment margin is quantitatively important, accounting for two-thirds of the aggregate decline in routine task content of vocational skill supply over the past five decades.

Third, curriculum updates generate sizable returns for new-skilled workers, consistent with these new skills being both demanded and scarce. Labor market entrants trained under updated curricula earn up to 4.1% higher wages than those trained under outdated curricula in the same occupation (comparable in magnitude to one additional year of labor market experience), rising to 6.3% for technology-exposed occupations. These workers also remain employed in their trained occupation at higher rates and sort into higher-paying firms, though substantial wage gains persist even within firms of similar pay, indicating that updated skills, not firm sorting, drive most of the return. Firms exposed to workers with updated skills also increase capital investments, particularly in technology-exposed occupations, consistent with capital-skill complementarity as one mechanism amplifying these returns. These gains reflect absolute improvements in wage trajectories—faster growth for new-skilled cohorts, not deterioration among comparison cohorts—and are not explained by changes in trainee or training firm composition.

Fourth, new skill supply has distributional consequences. Older occupational incumbents experience relative wage declines when new-skilled workers enter their occupation, consistent with skill obsolescence driven by competition with new-skilled entrants or by incumbents' skill mismatch with firms' updated production technology: after five years, wages fall by 3.4% for incumbents aged 50–59 and 1.9% for those aged 40–49 compared to incumbents not exposed to new-skilled workers. These losses partly reflect increasing employment at lower-paying firms—the mirror image of new-skilled entrants' upward firm sorting—though within-firm losses remain. We find only a weak formal firm-training response for incumbents, consistent with the wage losses we document. Younger incumbents do not experience wage losses but respond by switching out of updated occupations more frequently.

Our study contributes to several literatures. A first considers how technology shapes

the long-run evolution of skill demands, occupational structure, and wages (e.g., Goldin and Margo 1992; Katz and Murphy 1992; Acemoglu 1998; Autor et al. 1998; Katz and Autor 1999; Krusell et al. 2000; Card and Lemieux 2001; Goldin and Katz 2008; Autor et al. 2020; Acemoglu and Autor 2011; Acemoglu and Restrepo 2018, 2019; Autor et al. 2024). This literature establishes that technology reshapes skill demand by displacing labor from some tasks, complementing labor in others, and creating entirely new labor-using tasks. We provide the first systematic, long-run evidence of how skill *supply* adapts to these shifts through educational content, not just educational attainment. This adjustment margin is quantitatively important, driven predominantly by new skill acquisition, and causally linked to worker outcomes.

Second, we contribute to a literature documenting within-occupational task change, which shows that such changes—rather than compositional shifts across occupations—account for the majority of aggregate skill demand shifts (Spitz-Oener, 2006; Atack et al., 2019). This includes the emergence of new tasks within occupations (Lin, 2011; Autor et al., 2024), which Autor et al. (2026) show command a wage premium reflecting the scarcity of the expertise these tasks demand. We advance this evidence in two ways: we identify curriculum adaptation as a mechanism through which this novel expertise is produced, and provide causal evidence on the returns to acquiring this expertise. This literature has also developed multidimensional demand-side measures of occupational human capital from job vacancies and task descriptions (Atalay et al., 2020; Deming and Noray, 2020; Li et al., 2021; Acemoglu et al., 2022; Deming, 2023; Hemelt et al., 2023). We develop an analogous multidimensional measure on the labor supply side, establish technological change as a causal driver of within-occupational skill supply adjustments, and show that these adjustments account for the majority of aggregate supply-side change—paralleling the demand-side finding.

Third, we contribute to a literature on skill obsolescence (Neuman and Weiss, 1995; MacDonald and Weisbach, 2004; Janssen and Mohrenweiser, 2018; Deming and Noray, 2020; Fillmore and Hall, 2021; Kogan et al., 2023). Most closely related, Janssen and Mohrenweiser (2018) document that a single German curriculum update—in response to CNC machinery adoption—deteriorated incumbent outcomes in one occupation. We extend this evidence to the near-universe of German vocational occupations and all technologies these occupations are exposed to, and identify the causal effect of technology on curriculum change. Distinct from this literature's focus on old-skilled incumbents, we also identify the gains to new-skilled workers. This matters because obsolescence and expertise creation need not co-occur: incumbents' skills may become obsolete without a corresponding gain to new cohorts, for

instance if the displaced expertise is now embodied in technology and hence no longer scarce.

Fourth, we contribute to an emerging literature on educational content change. Curriculum and major choices are a significant source of human capital heterogeneity (Altonji et al., 2012), and a growing body of work examines how educational programs respond to shifting labor and student demand (Conzelmann et al., 2023; Light, 2024). Within higher education, Boustan et al. (2022) document that universities introduce more CNC-related degree programs following this technology's adoption; at earlier stages of education, Hermo et al. (2022) document a shift in Swedish primary school curricula from factual knowledge toward reasoning skills; regarding on-the-job training, Adhvaryu et al. (2023) show that firms respond to new product models by upskilling their workforce in problem-solving skills. Most closely related, contemporaneous work by Biasi and Ma (2026) shows that college courses closer to the academic research frontier improve students' educational attainment and earnings—establishing that content proximity to the knowledge frontier matters for student outcomes in U.S. higher education. We instead focus on non-college training over five decades, and highlight the role of technological change in producing these updates. We also study the consequences for incumbent workers when their occupation absorbs newly updated expertise.

Also using German apprenticeship curricula, Langer and Wiederhold (2025) measure the level and specificity of skills taught within a single, current curriculum vintage, classifying skills as general or specialized based on when they are taught within each curriculum's training sequence. Comparing workers trained in different occupations, they find that most of the earnings premium to apprenticeship training is associated with general rather than specialized skills. We instead study how curriculum content adapts over time: we show that technological change is a causal driver of curriculum updates, and we estimate the causal returns workers gain from acquiring the resulting new skills.

A related broader literature catalogs curriculum skills across European vocational systems and their correlation with wages (Eggenberger et al., 2017; Kiener et al., 2022, 2023; Schultheiss and Backes-Gellner, 2024; Buehler et al., 2024; Cnossen et al., 2025). We contribute to these literatures by studying how exposure to new technologies affects curriculum content over five decades, and by identifying the causal impacts of this content change on worker outcomes—enabled by our comprehensive, longitudinal data on curriculum updates.

The remainder of this paper is structured as follows. The next section describes our data and measurement. Section 3 tests whether technological advances spur curriculum change, and documents the skill content of curriculum updates. Section 4 examines the labor market

impacts of vocational training updates for individual workers—separately for new-skilled entrants (Section 4.2) and occupational incumbents (Section 4.3). Section 5 concludes.

2 Data and measurement

We rely on three main data sources. The first two are training curricula and patent texts, which we link using Natural Language Processing (NLP) techniques. We describe these data sources below. The third comprises administrative data on firms and their workers, which we describe in Section 4, where we turn to the labor market impacts of curriculum updates.

2.1 Vocational training occupations and curricula

Institutional setting. In Germany, vocational training typically combines classroom schooling (1–2 days weekly) with on-the-job training at a firm (3–4 days weekly), known as the dual system. This full-time training is usually undertaken after high school and typically lasts three years, with a minority of vocational training programs taking two years or three and a half years. An external board of examiners—comprising equal parts representatives from employer associations, employee associations, and vocational school teachers— administers both the final written and practical exams, not the training company itself. Pass rates average 90%, so the examination is not a formality.[2]

Following the 1969 Vocational Training Act (Bundestag, 1969), virtually all dual training is codified in state-approved and nationally standardized training curricula, which are regularly revised through a well-defined and institutionalized process.[3] Employers (through individual firms, employer associations, or professional organizations called *Kammern*), employees (through labor unions), or the Federal Institute for Vocational Education and Training (*Bundesinstitut für Berufsbildung*, BIBB) can initiate updates to training curricula.[4] The parties involved have agreed to limit the duration of the process to approximately one year (Bundesinstitut für Berufsbildung, 2023), and another six months until legal enactment.

[2]Average over 2010–2022, based on DAZUBI data (Bundesinstitut für Berufsbildung (BIBB), 2022).

[3]Vocational training at vocational schools only, including training in health, education, social services, and vocational training to become a civil servant are not delivered in the dual system subject to the Vocational Training Act and therefore not included in our analyses. Overall, approximately 70% of all vocational trainees are trained within the dual system subject to the Vocational Training Act (BIBB, 2020).

[4]Vocational school curricula are developed in close coordination with the on-the-job training curricula that we study, and feature closely corresponding changes (Kultusministerkonferenz, 2021).

Curriculum updates thus arrive around 1.5 years after official initiation. For some updates, firms receive grace periods before they must comply with the new curriculum, while the majority of curricula take effect at the start of the next training year.[5] Implementation of new training content is supported through multiple channels: BIBB publishes implementation guides to help trainers implement new content following curriculum updates. Practical training components can take place in inter-company training centers (*Überbetriebliche Ausbildungsstätten*) when individual firms cannot provide these on their own. The *Kammern* further support implementation through information events for trainers and firms. Firms may in principle teach content beyond what the curriculum specifies, including new skills ahead of a curriculum update. If this were widespread, curriculum updates would represent little novelty for trainees and generate limited wage effects. The substantial returns we document below suggest this is not the case.

Appendix Table A1 shows reasons for updates over 2011–2021 based on 135 update proposals tabulated in Schad-Dankwart et al. (2023). Each update may have multiple reasons, such that the total frequency exceeds 135. Curriculum updates occur for a wide variety of reasons. Some are more procedural or administrative (such as changes to the examination format or structure, jointly mentioned 47 times; or conceptual design criteria, mentioned 34 times), but many also involve substantive reasons, including technological change (mentioned 115 times), changes in competences (mentioned 97 times, with growth of competences and decline of competences separately mentioned), and firm-level structural change (mentioned 40 times).

While this institutional setting uniquely allows us to observe curriculum content and its updates comprehensively over 50 years (as well as individual workers' skill vintage), changes in educational content are a common feature of education systems worldwide, enhancing the external relevance of our findings: in Appendix B.4 we use U.S. Classification of Instructional Programs (CIP) data to document widespread emergence of new degree programs over the past three decades.

Sample construction. Our analysis focuses on occupations with observed vocational train-

[5]In our data, 33 curriculum updates, i.e. 7% of observed updates, are granted a grace period of on average 15 months. For example, the new curriculum for Industrial metal occupations took effect in August 1987, but apprenticeships that began before December 1989 were still allowed to follow the old curriculum. Similarly, for the updated curriculum of Process mechanic for coating technology, which took effect in August 1999, a grace period was granted until December 1999.

ing curricula ('training occupations').[6] We build a training occupation by year panel over 1971–2021 containing training occupations with their occupation classification code and indicators of curriculum content and changes therein. The panel is unbalanced as training occupations only enter once the first post-1969 curriculum is observed and need not exist over the entire time interval.

To obtain training curricula and their changes, we proceed in three steps. First, we collect vocational training curricula in Germany by web-scraping the archives of the Federal Law Gazette.[7] These exist from 1971 onward, and specify the obligations and rights of both trainees and trainers for most dual vocational training programs. In total, we obtain 756 unique training curricula, characterizing 492 training occupations, defined as unique occupation titles.[8]

The Vocational Training Act requires that all training curricula include five elements: (1) the title of the training occupation, (2) the duration of the training, (3) the skills and knowledge to be acquired during the program, (4) a plan outlining the sequence and description of these skills and knowledge in great detail (called the training framework curriculum), and (5) the requirements for passing the final examination. The curriculum text is very elaborate, averaging 11.1 pages. We machine-translate curricula from German to English.[9]

Second, we match these curricula to a separate database containing entries for all curriculum changes ('Index of Recognized Training Occupations', or *Verzeichnis der Anerkannten Ausbildungsberufe*) based on training occupation title and year of issue. This allows us to link preceding training occupations to current and future training occupations when occupational titles changes. We match the large majority of data: for 48 curriculum changes mentioned in the registers, we do not observe the curriculum text; and 28 scraped curricula cannot be matched to the register containing recognized training occupations.

Third, we match training occupation titles to official occupation codes from the 2010 German classification system (*Klassifikation der Berufe*, KldB) at the 4-digit level using a crosswalk provided by the BIBB (Lohmüller, 2021).[10] The 492 training occupations link to

[6] While not all workers employed in these occupations hold a vocational training diploma, on average 78% do. Averages over 1975–2021, based on the SIAB.

[7] *Bundesgesetzblatt*, archives available online at `https://www.bgbl.de/`.

[8] Several documents contain training programs for more than one occupation: we split these to obtain separate occupational curricula.

[9] We use GoogleTranslator from the Python package deep_translator.

[10] The assignment of training occupations to KldB occupations is not always one to one. For the analyses in

237 distinct KldB occupations (henceforth: occupations).[11]

Indicators of curriculum updates. We derive different indicators on curriculum content and changes at the training occupation by year level. Our baseline indicator is a binary variable equal to 1 if the training curriculum was changed in a given year, and 0 otherwise. We further categorize these curriculum updates into four types: updates in curriculum content without changes in the number or names of training occupations; updates in curriculum content accompanied by a change in the name of the training occupation; updates in curriculum content accompanied by the aggregation of multiple training occupations into one; and updates in curriculum content accompanied by the segregation of a training occupation into several distinct programs.[12] We additionally characterize the skill content of curriculum changes by analyzing changes in textual descriptions, as described in Section 3.2.

Labor market context. To contextualize these jobs in the broader German labor market, Appendix Figure A2 shows separate boxplots of wages for training occupations and for all other occupations. The median real training occupation wage is around 100 euros daily, slightly below the 114 euros observed in other jobs. Daily wages in training occupations vary meaningfully with an interquartile range of 83 to 110 euros. This highlights that training occupations are middle- to low-paid jobs compared to other occupations in the German economy.[13] Collective bargaining coverage in Germany is below 40% (2018), lower than some other European countries like France or Italy, where it is closer to universal, implying that firms retain substantial discretion in wage setting (Jäger et al., 2025).

Section 3 this is not an issue as analyses are at the level of training occupations and KldB occupations are only used for fixed effects or clustering of standard errors. Here, when one training occupation is linked to multiple KldB occupations, we assign the KldB occupation that is assigned to the training occupation without specialization (*ohne Fachrichtung* or *Monoberuf*). For later analyses at the KldB occupation level, we employ a different approach, discussed in Section 4.

[11] The number is lower for two reasons. First, whenever a training occupation receives a new occupation title, we classify it as a new training occupation while the time-consistent KldB occupation does not change. Second, the match between training and occupations is not unambiguous such that in some cases, one KldB occupation covers multiple training occupations.

[12] The total number of updates is equal to the sum of content-only and other updates, but these other categories are not mutually exclusive: a training occupation may be split into several successors, each of which is an aggregation of multiple predecessors. Likewise, both aggregations and segregations may be accompanied by changes in the name of the training occupation. Hence, the sum of the number of content-only updates and those accompanied by renamings, aggregations, or segregations exceeds the total number of changes.

[13] Appendix Figure A3 presents the wage distributions of vocationally trained workers and for all other workers, showing the same pattern.

Table 1 lists the ten largest training occupations in our sample, based on employment counts. This includes Office clerks and secretaries, which have 10.6% share in total employment on average over 1975–2021; Occupations in warehousing and logistics; Occupations in machine-building and -operating; Retail sales occupations; Professional drivers (cargo trucks); and Technical occupations in automotive industries, which each have 3 to 4% employment share. While daily gross real wages vary between 151 euros for Occupations in electrical engineering and 71 euros for Retail sales occupations, nine out of ten of these occupations have experienced decreasing employment shares, with the strongest decline observed for Office clerks and secretaries (6 percentage points over 1975–2021), consistent with job polarization patterns documented for Germany (Goos et al., 2014).

2.2 Descriptives on training curriculum updates

To illustrate the nature of training curricula and their updates, Appendix Figures A1a through A1d show machine-translated excerpts of training curricula for two occupations, Process control electronics technicians (from the 1992 curriculum and its 2003 update) and Industrial clerks (from the 1978 curriculum and its 2002 update). These examples highlight both the detailed nature of these curricula and substantive changes over time.

Appendix Figure A1a shows that in 1992, Process control electronics technician apprentices had to learn to manufacture mechanical parts and make mechanical connections. Each of these skills is specified in further detail, where one part of the latter is "making connections using screws, nuts and washers and secure them with safety elements, in particular spring washers, toothed lock washers and paint". Figure A1b shows excerpts illustrating the 2003 update. Apprentices in the same training occupation (now named Electronics technician for automation technology) must learn to install and configure IT systems and advise and support customers. The former is further detailed as, among other things, "selecting hardware and software components", "installing and configuring operating systems and applications", and "integrating IT systems into networks". Further, "solving problems in a team" is now mentioned among operational and technical communication skills.

Industrial clerk training similarly shows important changes in its 2002 curriculum (Appendix Figure A1d) relative to its 1978 version (Appendix Figure A1c). In 1978, purchasing skills are described as "compiling, evaluating and supplementing purchasing documents", "processing offers", and "processing orders". In the 2002 update, specific reference is made to electronic procurement and electronic commerce; as well as using "standard software and company-specific software" and "entering data and information". There is also emphasis on

teamwork, planning, and organization.

Table 2 provides descriptives on training curriculum changes over 1971–2021. Panel A shows unweighted results. 3.8% of the 11,843 training occupation-year observations have experienced a curriculum update, with the majority only involving a content update ($0.021/0.038 \times 100 = 55\%$). 39% of updates additionally involve a renaming of the training occupation. Around a quarter of changes are accompanied by aggregations of preexisting training occupations. Only 33 training curricula involve occupational segregations, comprising 8% of all curriculum updates. Employment-weighted patterns in panel B are similar, but the annual curriculum update probability is 5.1% (compared to 3.8% in the unweighted data), reflecting that larger training occupations are more likely to receive updates.

Panel A of Figure 2 shows the total number of curriculum updates over time, i.e. the number of new curricula conditional on observing the training occupation's preceding curriculum, using five-year moving averages. There is a strong rise in curriculum change since the early 1990s, peaking around 2004 when 22 curricula were updated (corresponding to around 7% of training occupations at the time). This increase in curriculum change partly reflects the rising number of observed preceding curricula, as seen in panel B. In our analyses, we do not exploit this time series variation because it may also capture changing time investments in curriculum updating for administrative reasons: instead, we leverage the distribution of changes across training occupations within a given year.

Table 3 shows the most and least frequently updated training occupations in our data, as measured by the average number of curriculum changes within that occupation per year. Examples of occupations with frequent curriculum updates are Flexographers, Electronics technicians for automation technology, Industrial mechanics, Electricians, Retail clerks, Automobile mechanics, and Electronics technicians for aeronautical systems. By contrast, among occupations that updated at some point, the least frequently updated ones include Gardeners, Manufactured porcelain painter, Foundation engineering specialists, Civil engineers, Road builders, and Asphalt builders. Several occupations experience no curriculum change over our time window, including Brass instrument makers, Delivery drivers, Floor layers, Gilders, Glass blowers, Hotel clerks, Makeup artists, and Stage painters and sculptors.

Figure 3 characterizes the full distribution of curriculum update intervals. Panel A highlights substantial variation across curricula: some are updated within a few years, while others remain unchanged for two or more decades. On average, among curricula that are eventually updated, the average interval is 15.3 years, as seen from the bottom row of panel A in Table 2. Panel B shows that this varies substantially across broad occupation groups:

curricula for IT and scientific service occupations (comprising 5.7% of all curricula) update most frequently, followed by Business service occupations (8.8% of all curricula), Production occupations (64.6% of all curricula), and Other commercial service occupations (12% of all curricula), while Personal service occupations (9.0% of all curricula) update least frequently. There is substantial variation within each of the five broad groups.

2.3 Measuring technology exposure

We use U.S. utility patents as a measure of the flow of technological innovation, following a large literature (e.g. see Griliches 1981; Jaffe et al. 1993; Hall et al. 2001): patents are a detailed measure of the flow of technological innovation, though they do not capture all innovations, such as those less suited to protection as intellectual property.

We focus on the subset of U.S. utility patents which Kelly et al. (2021) classify as technological breakthroughs.[14] These breakthroughs are both novel (i.e. distinct from previous patents) and influential for subsequent innovation (i.e. similar to later patents), operationalized as the top 10% of patents by year in terms of forward-to-backward textual similarity. We lag breakthroughs by 20–25 years relative to our 1971–2021 curriculum data, considering technological breakthroughs occurring over 1946–2001. 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. We follow Autor et al. (2024), who use the same lag length for measuring occupational exposure to breakthrough patents.

Using lagged breakthroughs rather than all patents serves two purposes. First, breakthroughs are the most transformative technologies (Kelly et al., 2021), and therefore likely important for skill changes. This should increase signal in our technology measure. Second, identifying the impact of innovation on curriculum updates requires exogenous technological shifts. Reverse causality is a concern: new technology could emerge in response to contemporaneous shifts in skill supply as reflected by curriculum change. Moreover, contemporaneous demand shifts could drive both innovation and changes in skill supply, introducing simultaneity bias. Using technological breakthroughs helps address these concerns because they represent unexpected and discontinuous changes in innovation while being predictive of subsequent patenting flows (see Autor et al. (2024) who developed this identification strat-

[14] Major technologies are patented in both the U.S. and in Germany: we use U.S. patents to leverage Kelly et al. (2021)'s established classification of technological breakthroughs. From 1976 onward, we observe the nationality of inventors in PatentsView: 2.7% of U.S. breakthrough patents are held by German inventors.

egy and provide supporting evidence). We explore the lag structure using local projections (Jordà, 2005) below.

In our baseline models, we focus on digital technologies, though we show robustness using breakthrough patenting activity across all technology classes. Figure 4 shows the distribution of breakthrough patents across eleven broad technology classes as defined by Kelly et al. (2021) over time. The technology class "Instruments & Information", capturing digital technologies, has seen the largest expansion of breakthrough patenting over 1946–2021.[15] Towards the end of the period, these technologies comprise the majority of all patenting (Autor et al., 2024), reflecting the Digital Revolution.

Linking curricula to patents. We measure each training occupation's technology exposure by linking each curriculum in year t to the textual content of breakthrough patents emerging over $[t-25; t-20]$. We use the entire text of both machine-translated training curricula and patents.[16] Curricula describe skills and tasks rather than technologies by name, so we rely on semantic similarity via word embeddings rather than keyword searches— an approach that detects technology linkages even when specific technologies are not explicitly mentioned. We follow Seegmiller et al. (2023)'s linking method and first retain verbs and nouns excluding standard stopwords plus a small number of source-specific stopwords to compute Term-Frequency Inverse-Document-Frequency (TD-IDF) weighted averages of pre-trained word embedding vectors provided by Pennington et al. (2014). We then obtain the cosine similarity between every patent-curriculum pair, and normalize these similarity scores by subtracting the median similarity for each patent (as in Autor et al. 2024) to avoid assigning low similarities to patents using more technical language.

Appendix Table A3 shows the most similar digital breakthrough patent for several example curricula, revealing sensible linkages. For example, "Self-gauging sensor assembly" (a sensor assembly for generating signals in response to the rotation of a body) is the most similar patent for the curriculum of Body and vehicle builders; "Process for making a prosthetic implant" is the most similar patent for the curriculum of Dental technicians; and "Computer travel planning system" is the most similar patent for the curriculum of Travel agents. Finally, we retain the 15% most similar patent-curriculum pairs (following Autor et al. 2024), and sum them for each curriculum: the resulting occupational patent count is

[15] 2.1% of U.S. digital breakthrough patents since 1976 are held by German inventors.

[16] Patent texts are obtained from Autor et al. (2024). Appendix Table A2 shows the number of tokens contained in curriculum texts used for matching to patent texts—the average curriculum has 43,001 tokens.

our measure of technology exposure. We perform this procedure separately for all patents and for the subset of digital patents, where the latter measure is our baseline.

Variation in technology exposure. Training occupations vary widely in their exposure to technological change embedded in patents, as illustrated by the distribution of linked digital breakthrough patents across occupations in panel A of Figure 5. Appendix Table A4 reports descriptive statistics on technology exposure. We will exploit this occupational variation in technology exposure within years to study technology's impact on educational content of training curricula. Panel B of this figure reports the number of linked patents separately for each of the five broad occupation groups. Technology exposure is highest for IT and scientific service occupations, followed by Production occupations, and lower for Other commercial service occupations, Business service occupations occupations, and Personal service occupations. Appendix Figure A4 highlights that overall and digital technology exposure are strongly positively correlated in both halves of our 50-year period.

Table 4 provides further examples of the most and least digital technology-exposed training curricula in our data. Highly exposed curricula include various types of Electronics technicians (for machines and drive technology, for industrial engineering, for devices and systems, for building and infrastructure systems, for information and system technology, and for automation technology), Industrial mechanics, Cutting machine operators, Plant mechanics, and Tool mechanics. Jobs with low exposure to digital technology include various service occupations such as Factory firemen, Ice cream specialists, and Bespoke shoemakers, as well as production occupations like Leather production and tanning technology specialists, Candle and wax makers, Confectionery technologists, Wine technologists, and Concrete and terrazzo manufacturers. Appendix Table A5 shows the most and least exposed occupations separately for each of the five broad occupational groups. For example, for business service occupations, Media designers are among the most exposed while Pharmaceutical clerks are among the least exposed.

Our patent-based technology exposure finds direct support in the subsample where we observe stated reasons for curriculum updates. Using BIBB-provided data on update proposals since 2011 that record whether technological change was cited as a reason, we observe that 85% of the 135 proposals in this period cite technological change as a reason, of which 29% specifically cite digitization, see Appendix Table A1. Updates citing digitization as a reason have significantly higher digital technology exposure than other updates (on average 382 linked patents versus 178, $p = 0.03$ based on a one-sided t-test), confirming that occupations our patent-based measure identifies as highly exposed to digital technology are indeed

updating in response to digitization.

3 Does technology exposure spur curriculum change?

This section examines whether technology exposure spurs curriculum change. We first analyze whether occupations more exposed to breakthrough digital technologies update their training curricula more frequently (Section 3.1). We then examine the skill content of these updates (Section 3.2). Section 4 turns to labor market outcomes.

3.1 Technology exposure and curriculum updates

Figure 6 presents a Kaplan and Meier (1958) survival plot separately for high- and low-technology exposed curricula. "Survival" means the curriculum has *not* yet been updated. The figure shows that high-technology exposed curricula update more rapidly: 15 years after initial observation, around 70% of curricula with low technology exposure (below-median) remain unchanged, compared to only 40% for those with high technology exposure (at- or above-median exposure). While this approach accounts for right-censoring, it does not control for other factors.

We thus estimate whether digital technology exposure spurs curriculum updates using the annual panel of training occupations:

$$\mathbb{1}(\text{Update})_{kjt} = \beta \text{Tech}_{kj,[t-25;t-20]} + \gamma_t + \theta_{kj,\tau} + \zeta_{J(\times t)} + \delta \frac{E_{jt_0}}{E_{t_0}} + \varepsilon_{kjt} \ , \tag{1}$$

where k indexes curricula, j training occupations, t calendar years, and τ the first year a curriculum is observed. The dependent variable equals one when training occupation j updates its curriculum k in year t, and zero otherwise. Our key independent variable, $\text{Tech}_{kj,[t-25;t-20]}$, measures the digital technology exposure of each training occupation's curriculum k through the log count of textually linked digital breakthrough patents in a five-year window 20 years prior.

We include calendar year fixed effects (γ_t) to absorb year-specific variation in both curriculum updates (for example for institutional reasons) and patent linkages (since patent counts grow over time). We control for each training occupations' curriculum inception year ($\theta_{kj,\tau}$) in five year bins, since training occupations enter the data at different points in time. Some specifications add broad occupation fixed effects or broad occupation by year fixed effects ($\zeta_{J(\times t)}$). We also control for occupations' initial 1975 employment share ($\frac{E_{jt_0}}{E_{t0}}$) to ad-

dress concerns that larger occupations receive more frequent curriculum updates.[17] Standard errors are clustered by occupation (236 clusters). We expect $\beta > 0$, reflecting that training occupations that are more exposed to digital technology are more likely to experience a curriculum update.

Table 5 presents results, with panel A showing unweighted models and panel B models weighted by initial occupational employment shares. Across all specifications, we find that technology exposure spurs curriculum updates: a doubling in the exposure increases the probability that a curriculum is updated by 0.30 (=0.44 $\times$ ln(2)) to 0.35 (=0.51 $\times$ ln(2)) percentage points in the unweighted models, and 0.55 (=0.79 $\times$ ln(2)) to 0.58 (=0.84 $\times$ ln(2)) percentage points in the ones weighted by occupational employment. These estimates remain stable when controlling for broad occupation fixed effects (column 2) and broad occupation by year fixed effects (column 3), confirming that technology exposure drives curriculum updates *within* occupation groups. Results are also robust to controlling for occupational employment size (column 4).

These effects are economically meaningful. As reported in Appendix Table A4, digital technology exposure has a standard deviation of 2.58 in our unweighted panel. A one standard deviation increase in exposure therefore raises the annual curriculum update probability by 1.26 percentage points (0.49 $\times$ 2.58, column 4)— a 33% increase relative to the baseline update rate of 3.8% (shown in Table 2). Employment-weighted models yield somewhat larger effects: a one-standard-deviation increase raises the update probability by 2.12 percentage points (0.82 $\times$ 2.59, column 4), a 42% increase relative to the weighted baseline of 5.1%.[18] Appendix B.1.1 confirms the relevance of technology exposure in spurring updates using a duration model, which accounts for the survival structure of the data. In Appendix B.1.2, we show that technology exposure also accelerates how quickly updates arrive among the updated set, i.e. considering only the intensive margin of curriculum updates. A one standard deviation increase in technology exposure reduces time to update by 1.6 years, or 11% relative to the mean duration of 15.3 years. Appendix B.1.3 presents several robustness checks on our baseline results, including using only the exam section for linking curricula to patents which yields somewhat smaller coefficients because the exam sections contain less text; using breakthroughs in all technology classes rather than only those related to digital

[17] These occupations are not exactly one-to-one with training occupations as outlined in footnote 10.

[18] Results are also robust to restricting these models to occupations which are updated at least once; and to excluding potentially 'dying' occupations, defined as those with a reduction in the number of training contracts by more than half over time.

technology; presenting results separately by type of update; and exploring the time lag between breakthroughs and curriculum change using local projections.

3.2 Changes in curriculum content

Having established that technology exposure drives curriculum updates, we now examine how training content evolves. We also decompose curriculum changes into newly added versus removed terms, to distinguish between curricula where new skills have been added and those where the skill set has dwindled.

3.2.1 Non-routine task content

We next study how curriculum updates affect the routine intensity of training, an omnibus measure of digital technology's impact on task content. Routine tasks can be codified in digital technology (Autor et al. 2003), and a large literature documents that digital technologies replace workers in routine tasks while complementing them in non-routine ones (e.g. see Autor et al. 2003, 2006; Autor and Dorn 2013; Goos et al. 2014). Vocational training curricula should therefore become less routine-intensive over time if digital technology is an important driver of curriculum updates. We expect this decline to be more pronounced among highly technology-exposed occupations.

To measure curriculum task content, we leverage NLP methods. We use O*NET task descriptions for routine and non-routine task items across all occupations to construct TF-IDF-weighted vectors of word embeddings for five task measures: routine cognitive tasks, routine manual tasks, non-routine manual tasks, non-routine analytic tasks, and non-routine interpersonal tasks.[19] We then measure cosine similarity between training curricula vectors (as constructed before) and these task vectors: high cosine similarity indicates strong textual similarity between a curriculum and a task.[20]

We define non-routine task intensity as the sum of a curriculum's cosine similarities to the three non-routine tasks, minus the sum of its similarities to the three routine tasks.

[19] We adopt Acemoglu and Autor (2011)'s O*NET items for the task measures whenever these items have more detailed textual descriptions available— these descriptions are required for textual linking to curriculum text. Appendix Table A6 lists specific O*NET items used for each of the five task groups.

[20] Because this procedure links curricula to general task descriptions rather than to occupation-specific tasks, it does not require a crosswalk between US and German occupations.

Non-routine task intensity (NRTI) for training curriculum k is therefore:

$$\text{NRTI}_k = (CS_{k,NRM} + CS_{k,NRA} + CS_{k,NRI}) - (CS_{k,RM} + CS_{k,RC}) \ ,$$

where $\text{CS}_{k,i}$ indicates the cosine similarity between curriculum k and task i, with $i \in$ {NRM, NRA, NRI, RM, RC}. NRM are non-routine manual tasks, NRA non-routine analytic tasks, NRI non-routine interpersonal tasks, RM routine manual tasks, and RC routine cognitive tasks.

Appendix Table A7 shows the most non-routine intensive and most routine intensive curricula cross-sectionally. Among the most non-routine intensive curricula are those for Sports specialists, Personnel services clerks, Marketing communication clerks, Market and social research specialists, and Event managers. By contrast, among the most routine intensive are curricula for Embroiderers, Confectioners, Glassmakers, Dressmakers, Clothes tailors, Bakers, and Basket makers.[21] These occupational non-routine task intensity rankings are consistent with the literature, giving us confidence that our methodology accurately captures curricula's non-routine task content.

We estimate descriptive models in the training occupation by year panel:

$$\text{NRTI}_{kjt} | \{\mathbb{1}(\text{Update})_{kj}\} = \beta t + \delta_j + \varepsilon_{kjt} \ , \tag{2}$$

where NRTI_{kjt} is the non-routine task intensity of curriculum k for training occupation j in year t. The coefficient β on the linear time trend captures the average annual change in non-routine task content (in standard deviations) across curricula. Since content changes occur by definition at the intensive margin, we estimate equation (2) for updated curricula only— those that have potentially changed their skill content. We include 4-digit occupation fixed effects δ_j to account for changing occupational composition over time,[22] and cluster standard errors by 4-digit occupation. This requires dropping the first five years of data (when we do not observe any curriculum updates), yielding a sample covering 1976–2021.

We also estimate equation (2) separately for training occupations with above-median versus at or below-median technology exposure, measured in the year each curriculum was

[21] Appendix Table A8 shows the most non-routine intensive and most routine intensive curricula separately for each of the five broad occupation groups. Appendix Figure A5 shows that routine task intensity is negatively correlated with occupational employment growth, as expected.

[22] This results from the growing number of curricula, see panel B of Figure 2.

first observed to avoid including endogenous changes in curriculum content. We expect β to be positive and larger for highly technology-exposed occupations.

Figure 7 plots estimates of β (and 95% confidence intervals), showing a clear upward trend in curricula's non-routine task intensity. Annually, NRTI increases by 0.041 standard deviations, totaling 1.8 standard deviations cumulatively over 1976–2021. This trend is more pronounced for technology-exposed occupations, where RTI rises by 0.057 standard deviations annually (i.e. 2.6 standard deviations cumulatively over 1976–2021), compared to 0.022 standard deviations annually (1.0 standard deviation cumulatively) for less technology-exposed curricula. Curriculum updates thus equip workers with training in more non-routine intensive tasks, especially in occupations highly exposed to digital technologies.

Figure 7 also reveals that the overall trend holds in both production and service occupations, even though the increase is somewhat more pronounced among production occupations, which constitute two thirds of training curricula. The increase for technology-exposed curricula is of similar magnitude for both production and service occupations (although the estimate for service occupations has a larger confidence interval). [23,24]

Two additional pieces of evidence corroborate this pattern. Using independent, text-based measurement approaches, Appendix B.2 shows that curricula increasingly incorporate digital- and social-skill keywords, particularly in technology-exposed occupations (Appendix B.2.1), and that curriculum vocabulary becomes more complex over time, consistent with the accumulation of scarce expertise (Autor and Thompson, 2025) (Appendix B.2.2).

How important are curriculum updates for shifting overall skill supply? To quantify this, we use representative labor market data (SIAB) to compute the number of vocational trainees in West Germany per occupation and year, and assign each trainee their training occupation's curriculum-based non-routine task intensity. We decompose the total change in non-routine task intensity between 1976 and 2021 across occupations into two components: the within-occupation curriculum component, holding occupation shares constant, and the between-occupation component, holding curriculum content constant.[25] The non-routine

[23] Results are virtually identical when we additionally control for the number of tokens contained in each curriculum, removing any potential mechanical association between the time trends in curriculum length and in non-routine task intensity.

[24] All results for NRTI reported in this section also hold when using tasks from the German Qualification and Career Survey (QCS) instead of O*NET tasks to construct task vectors.

[25] We compute $\Delta\text{NRTI}_{1976,2021} = \sum_j \Delta\text{NRTI}_{j,1976,2021}(w_{j,1976} + w_{j,2021})/2 + \sum_j \Delta w_{j,1976,2021}(\text{NRTI}_{j,1976} + \text{NRTI}_{j,2021})/2$, with w_j occupation j's trainee share in the respective year (i.e. the share of all trainees training in this occupation). For years before we observe an occupation's first curriculum, we use the non-

task content of vocational skill supply increased by 0.95 standard deviations over these 45 years, with 0.63 standard deviations (66.0%) stemming from the within-occupation component,[26] and the remainder reflecting the changing occupational composition of trainees. Within-occupation skill adjustments through curriculum updates thus account for two-thirds of the aggregate change. This parallels previous findings that within-occupation task changes dominate aggregate skill demand shifts (Spitz-Oener, 2006), underscoring the importance of the within-occupation skill supply adjustment margin we study here.

These changes in curriculum content do not only closely resemble technology-driven shifts in skill demand documented in the literature; we also find direct evidence that curriculum updates make training more useful to workers. Using German Qualification and Career Survey (QCS) data, Appendix B.3 shows that workers trained under more recently updated curricula report finding their training more useful for their current jobs. Whether this added relevance translates into labor market returns is the central question of Section 4. Prior to that, we examine whether these content changes reflect the emergence of new expertise, rather than simply the removal of old content.

3.2.2 New skill emergence and skill removal

Changes in vocational skill content may arise from the addition of new skills ('new skill emergence'), changes in the relative weight of existing skills ('skill reweighting'), the removal of skills ('skill removal'), or some combination thereof.[27] These mechanisms may have different implications for workers: acquiring a narrower skill set than prior trainees (for example because some tasks are automated), is less likely to be beneficial, than (also) acquiring new expertise.

To study this, we extract removed words and newly added words for each curriculum update, with words including verbs and nouns as before.[28]

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routine task intensity of the occupation's first observed curriculum. This arguably yields a conservative estimate of the within-occupation component.

[26] The resulting cumulative increase in NRTI is smaller than that implied by the linear time-trend regression reported above because the latter multiplies the estimated annual within-occupation trend by fifty years, effectively extrapolating it across periods in which some curricula are not observed.

[27] Buehler et al. (2024) study curriculum design by considering removed and added word shares in Swiss curricula.

[28] In our baseline results presented here, we count as new any word that has not occurred in the previous curriculum of the training occupation, and as removed any word not found in the newly updated curriculum. To ensure that new and removed words are not the result of noise due to for example misspellings or OCR-

Appendix Figure A6 shows that curriculum updates involve substantial word removal and addition. Across all five occupation groups, an average curriculum update involves almost 200 distinct words being removed and around 170 distinct new words being added (panel A), corresponding to 35–45% of the total distinct curriculum word (panel B).[29]

Importantly, skill reweighting, skill removal, and new skill emergence play distinct roles in changing curricula's non-routine task intensity. Figure 8 plots the non-routine task intensity of the previous curriculum's remaining words (horizontal axis) against the non-routine task intensity of three separate components of the new curriculum (vertical axis): words present in both curricula but with potentially different frequency ('remaining words'), words removed in the update, and words added in the update. Each observation represents a curriculum update, and local polynomial plots are shown for each component. Observations on the 45-degree line indicate that a component of the new curriculum has the same non-routine task intensity as the previous curriculum's remaining words, leaving overall routine task intensity unchanged. Observations above (below) the line indicate that the component of the new curriculum is higher (lower) in non-routine task intensity than the previous curriculum, shifting it to be less (more) routine-intensive.

We find that newly added words play an outsized role in increasing curriculum non-routine task intensity: the orange-colored data lie most strongly above the 45-degree line in both panels. At all levels of previous non-routine intensity, newly added words make updated curricula more non-routine intensive. This effect is particularly pronounced for curricula with the lowest initial non-routine intensity. Skill reweighting tends to increase non-routine task intensity, though to a lesser extent, especially for curricula that are already relatively non-routine intensive. Skill removal has a heterogeneous effect on non-routine task intensity, increasing non-routine intensity only for occupations that were initially less non-routine.

Given the importance of new skill addition, Figure 9 examines the skill content of newly added relative to removed words by classifying them into European Skills, Competences, Qualifications and Occupations (ESCO) skill categories. (Methodological details are in Appendix A.2.) A positive value indicates that curriculum reforms shifted relative emphasis

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related errors, both measures are conditional on new and removed words being words found in a library of 466 thousand English words from https://github.com/dwyl/english-words/blob/master/words_alpha.txt. Our results are robust to only counting as new or removed the subset of words that are sufficiently distinct from pre-existing and remaining words using a library of synonyms. Synonyms are identified using WordNet.

[29] Appendix Figure A7 shows that word removal and addition are not strongly correlated across curriculum updates, but do vary substantially.

toward this skill category; a negative value indicates the opposite— bars sum to zero. The figure shows a clear pattern: curriculum reforms shifted emphasis toward cognitive and interpersonal skills and away from physical and technical ones, as well as basic skills. The largest positive effect is in social & communication skills, which includes skills such as collaborating in teams, negotiating, and presenting information. Digital skills—covering areas such as programming, setting up computer systems, and using digital tools for collaboration and problem solving—and thinking skills, such as thinking creatively and processing information, also gained emphasis. Management skills, including developing objectives and strategies, organizing and scheduling work, and making decisions, show a similar positive shift. At the other end, physical and manual skills—such as moving and lifting, building and repairing structures, and sorting and packaging goods—show the largest decline, followed by manufacturing and engineering skills, which include operating machinery, and installing and repairing equipment. Core skills such as working with numbers and mastering languages also declined. The remaining categories, spanning knowledge fields such as natural sciences, business, and arts and humanities, as well as skill areas like information skills and self-management, show smaller net changes.

The skill content of these changes underscores that curriculum reforms meaningfully recompose the skill bundle that new trainees acquire, through both new skill emergence and skill removal. In the next section, we directly test whether these skill updates reinstate labor's expertise for new labor market entrants with updated skills and erode it for occupational incumbents trained in the previous curriculum.

4 The labor market impacts of curriculum updates

If curriculum changes enable workers to meet evolving skill demands, labor market entrants trained with updated curricula should fare better in the labor market than those trained in outdated ones (Section 4.2). Conversely, occupational incumbents should experience skill obsolescence when vocational training is updated (Section 4.3). We test these predictions separately using two distinct difference-in-differences designs, each applied to a distinct sample: one comparing successive cohorts of entrants in updating versus non-updating occupations, and one following individual incumbents over time in updating versus non-updating occupations—corresponding to the two labor market outcomes shown in Figure 1. Separate identification is important because reinstatement and obsolescence are different effects on distinct populations that need not co-occur: incumbents' skills may become obsolete without

corresponding gains for new cohorts.

4.1 Sample construction

We use SIEED data (Berge et al., 2020) as our primary employer-employee dataset.[30] SIEED is a 1.5% random sample of German firms with linked employee information from administrative records provided by the Institute for Employment Research (IAB). The data contain all workers ever employed by sampled firms plus pre-estimated AKM firm fixed effects (Abowd et al., 1999). For these workers, we observe complete employment biographies between 1975 and 2018, including wages and occupation, as well as industry and location of employing firms. While we do not observe unemployment, we observe non-employment, defined as not being employed in a job with mandatory social security contributions.

The data contain apprenticeship training spells, which indicate when workers start and complete their training program and which occupation they train in. For workers whose training spell we observe, this allows us to determine which curriculum vintage they were trained in when combined with our curriculum dataset. Since training occupations do not map one-to-one to KldB occupational codes provided in SIEED (as discussed in Section 2.1), we adopt the following approach. For KldB occupations (henceforth: occupations) comprising multiple training occupations, we classify workers employed in that occupation as having updated skills when at least one of underlying training occupation curricula updates. For training occupations linked to multiple occupations, we classify workers employed in all associated occupations as having updated skills.

We construct two separate worker samples for analysis. The first comprises labor market entrants—vocationally trained workers in the first five years after completing their training—whom we use to estimate the returns to updated skills (Section 4.2). We restrict this sample to workers whose training curriculum we observe, dropping workers trained before the start of the data (1975), and workers not trained in West Germany, because training curricula before German reunification apply only to West German apprentices.

The second comprises occupational incumbents—workers employed full-time in the same occupation for at least five consecutive years before a curriculum update—whom we use to estimate skill obsolescence (Section 4.3). Entrants and incumbents do not overlap by

[30] SIEED data access was provided on-site at the Research Data Centre (FDZ) of the German Federal Employment Agency at the Institute for Employment Research, and subsequently through remote data access.

construction. Appendix A.1 provides further details on data construction.

For occupational employment descriptives (including when using these as control variables) discussed in Section 2.1, we use SIAB data (Graf et al., 2023).[31] These data contain the same variables as SIEED but are a 2% random sample of individuals instead of firms. Given their representativeness at the worker rather than firm level, these data are better suited for describing the occupational employment distribution. For our main worker-level analysis, we rely on SIEED instead because it contains considerably more individuals (5.6 million compared to 1.8 million in SIAB data) and spells (173 million compared to 46 million in SIAB data).

4.2 Do curriculum updates reinstate worker expertise for new-skilled entrants?

4.2.1 Empirical approach

To identify whether curriculum updates reinstate worker expertise, we focus on the population directly affected by changes in training content: labor market entrants, defined as vocationally trained workers in the first 5 years after completing their training. We employ a difference-in-differences event study design comparing outcomes for cohorts of entrants trained before a curriculum update to cohorts of entrants trained after the update in the same occupation, relative to the corresponding entrant cohorts in occupations where no update occurred around the same time.

We estimate:

$$Y_{ijte} = \sum_{\substack{c=-5 \\ c\neq -1}}^{5} \beta_c \, \text{Update}_{je} \times I_{ce} + \sum_{c} \alpha_c I_{ce} + \delta_{je} + \gamma_{te} + \mu_e X_{it} + \varepsilon_{ijte} \ , \tag{3}$$

where Y_{ijte} is an outcome for entrant i who has been trained in occupation j, observed in calendar year t within event e.

Update_{je} is a treatment dummy indicating whether occupation j is the updating occupation in event e: this separates our treatment group (entrants trained in occupations with curriculum changes) from our control group (entrants trained in occupations without cur-

[31] SIAB data access was provided on-site at the Research Data Centre of the German Federal Employment Agency at the Institute for Employment Research, and subsequently through remote data access.

riculum changes in a window of 5 years before and 5 years after the treatment occupation's update).[32] c denotes cohorts of entrants defined by the start year of their vocational training relative to the year of the curriculum change, so that I_{ce} indicates whether entrant i belongs to cohort c in event e. We normalize $c = 0$ to represent the first cohort trained in the new curriculum:[33] thus, all treated cohorts $c \geq 0$ have been trained in the new curriculum, while treated cohorts $c < 0$ have been trained in the old curriculum. We restrict the sample to entrant cohorts whose training started in a window of 5 years before and 5 years after the treatment occupation's update, i.e. $c = [-5, 5]$.

This approach uses repeated cross-sections of entrant cohorts since pre-training (i.e. pre-treatment) labor market outcomes do not exist.[34] The first difference in our difference-in-differences strategy is the difference in outcomes between cohorts of entrants trained in the old curriculum and 'new-skilled' cohorts (entrants trained in the new curriculum) within the same occupation. The second difference compares entrants trained in occupations that updated their curriculum to entrants trained in occupations that did not update over the same time window.

Treatment is staggered because different curricula update in different years, so we cannot use the standard two-way fixed effect estimator (as shown in Callaway and Sant'Anna, 2021; de Chaisemartin and D'Haultfoeuille, 2020; Sun and Abraham, 2021; Goodman-Bacon, 2021). Instead, we stack observations for different events (i.e. different curriculum updates) following Cengiz et al. (2019).[35] This stacking implies that entrants and occupations can occur multiple times in the data as controls; and occupations can occur multiple times as treated, if their training curriculum updates more than once.

We control for cohort fixed effects ($\sum_c \alpha_c I_{ce}$), calendar year by event fixed effects (γ_{te}), and training occupation by event fixed effects (δ_{je}) as well as worker characteristics (X_{it})— age, and gender— interacted with event dummies. We cluster standard errors at the level

[32] Treatment is defined by the occupational training workers have received, not the occupation of employment after finalizing training. Since occupational choice is an outcome, we study this as a potential margin of adjustment.

[33] We use the curriculum update year including any grace periods: our results are similar when not incorporating grace periods but effects emerge somewhat more slowly as expected.

[34] The vast majority of trainees start vocational training right after school without any prior labor market participation.

[35] Baker et al. (2022) show that a stacked difference-in-differences setup recovers the true treatment effects in the case of staggered timing, just as the Callaway and Sant'Anna (2021) and Sun and Abraham (2021) approaches do. Other recent papers using this setup include Goldschmidt and Schmieder (2017); Deshpande and Li (2019); Clemens and Strain (2025); Bessen et al. (2025).

of treatment: occupation by event.

For each event, we draw 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. We drop a small number of events with fewer than 20 treated workers: this leaves a total of 357 curriculum update events, with 280,068 unique treated workers and 314,796 unique control workers, all of whom are labor market entrants. Control group workers are weighted by $1 \times N_{\text{treat}}/N_{\text{control}}$, with N_{treat} the number of treated observations per event and N_{control} the number of control observations per event. This is to ensure that events are weighted by the number of treated workers rather than giving more weight to those with higher numbers of control group workers relative to treated workers.

The parameters of interest are β_c, which capture the treatment effect relative to the pre-treatment cohort $c = -1$. We consider a range of worker outcomes: log daily wages, log annual earnings, non-employment, job mobility (across occupations, industries, and firms), firm AKM fixed effects (Abowd et al., 1999), and educational upgrading. For log wages, for example, we expect positive post-treatment estimates ($\beta_{c\geq 0} > 0$), reflecting that workers entering the labor market with updated skills earn higher wages over the first five post-training years than past entrants without updated skills, relative to entrants in control group occupations where no skill updates took place.

Identifying assumptions. Our identification rests on the fact that curriculum updates produce a discrete shift in skill supply at a known date, whereas technology-driven demand shifts evolve gradually (the dashed path in Figure 1). Any confounding demand effect would need to arrive discontinuously at the same time as the curriculum update. More formally, estimates of β_c can be interpreted as causal effects under three identifying assumptions: (i) parallel trends in the absence of curriculum updates, (ii) no anticipation of the curriculum update by (prospective) trainees or firms, and (iii) SUTVA.

We provide empirical support for these assumptions in several ways. First, we show that there are no significant pre-trends in entrant wages. Second, results are unchanged when controlling for each occupation's evolving technology exposure, which captures the gradual demand channel. Third, one might worry that curriculum updates increase student interest in pursuing those occupational training programs, potentially raising trainee quality and thereby affecting subsequent labor market outcomes. This would imply that wage impacts for entrants need not reflect returns to new skills. In Appendix D, we therefore extensively examine changes in trainee composition, finding no evidence of changes around curriculum updates, consistent with parallel trends and no anticipation. Likewise, we find no evidence

of differential firm selection into training around curriculum updates. Fourth, we find that curriculum updates induce wage effects. These effects are even larger at large firms, which are arguably more technologically advanced and thus more likely to train new skills beforehand. These findings point against anticipation effects, i.e. firms already providing the new skills before the update. Fifth, we show that positive wage effects for entrants are driven by faster wage growth for treated cohorts, not deterioration for control group cohorts—the latter would be expected under a SUTVA violation. We also confirm that results are robust to excluding from the control group those occupations with the highest worker mobility from the treated occupations. Last, we provide evidence that the pre-treatment entrant cohorts are also unlikely to have been directly affected, consistent with SUTVA. In Section 4.3, we study the impact of an influx of new-skilled entrants on *young* incumbent workers—the incumbent group most comparable to our pre-treatment entrant cohorts—and find no significant wage impacts.

Descriptives. Table 6 shows descriptives for our sample of vocationally trained labor market entrants within the first five years after training completion and the firms employing them, based on SIEED data. Vocationally trained labor market entrants are 23 years old on average, and 40% are female. Daily wages average around 67 euros, with a standard deviation of 31 euros. Most workers are employed year-round: the average number of days in employment is 268, with a median of 365. Workers are employed in relatively large firms of 560 workers on average, though workers' median firm size is 40 workers. This gap reflects our data being a random firm sample rather than a random worker sample. In our analyses below, we therefore also explore the role of firms and consider effect heterogeneity by training firm size. Appendix Table C2 shows corresponding descriptives for the stacked sample, separately for the $c = -1$ cohorts of treated and control group workers.

4.2.2 Wage impacts

Panel A of Figure 10 presents estimates of equation (3), using log daily wages as the dependent variable with β_c coefficients multiplied by 100 for legibility. There is no evidence of pre-trends (the p-value for a Wald test on the coefficients' joint significance is 0.25), consistent with treated and control cohorts of entrants following similar wage trajectories before curriculum reforms. Curriculum updates generate substantial wage returns over the first five years after graduation: 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% higher daily wages than old-curriculum graduates trained in the same occupation. These are workers trained for the same occupation under the same institutional conditions—the only difference is the curriculum vintage. This magnitude is economically meaningful—comparable to the 4.2% wage gain from one additional year of labor market experience among these vocationally trained labor market entrants.[36] Wage returns grow across entrant cohorts: this could result from firms progressively implementing the updated curriculum more fully or more effectively over time (for example due to adjustment costs), from complementary organizational change, or from complementary capital investments that updated skills subsequently induce (see Appendix E).

Panel B shows a very similar pattern for annual wage earnings, implying that effects are predominantly driven by the wage rather than employment margin—unsurprisingly, given the high labor force attachment of these labor market entrants. In further analyses of the labor market entrants, we therefore focus on daily wages as the outcome.

The positive wage returns indicate that curriculum updates equip entrants with skills that are valued in the labor market. The wage premium for obtaining new skills reflects an absolute improvement, not just a relative one; Appendix Figure C2 shows cohort estimates for treated and control group entrants, demonstrating that wage returns result from more rapid wage growth for treated entrant cohorts after the curriculum update, not slower wage growth for control group entrants.

A potential threat to causal identification is that curriculum updates attract different types of trainees or training firms, such that wage returns reflect improved cohort or training firm selection rather than returns to new skills. In Appendix D, we use data covering the universe of vocational trainees to document that curriculum updates do not impact occupational trainee composition in terms of prior high school education type, age, or gender, suggesting that wage increases for entrants are not driven by improvements in trainee characteristics following curriculum updates. Exam pass rates are also unchanged, as is program 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. Finally, Appendix Figure C3, panel A, shows that effects of curriculum updates on training firm quality, measured by AKM (Abowd et al., 1999) fixed effects, are negligible in size and mostly insignificant. Indeed, when studying wages net of

[36] Estimated for vocationally trained workers from a regression of individual log daily wages onto years of potential experience, controlling for firm AKM effects, dummies for large and small part-time jobs, a dummy for white collar occupations, a dummy for master craftsmen, and worker fixed effects.

training firm AKM fixed effects, effects remain almost unchanged in size and significance, see panel B—ruling out that wage returns are driven by entrants having been trained in higher-paying firms (for example because only such firms can more effectively implement updated curricula).

4.2.3 Mechanisms

The role of technology. To understand the mechanisms underlying improved wage outcomes for entrants with updated skills, we first examine how wage impacts vary with updated occupations' pre-update technology exposure. Technology exposure is one important driver of updates, as Section 3.1 establishes. But curriculum updates occur for various reasons, as Appendix Table A1 documents: 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 the 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. Other updates are less likely to do so.

Figure 11 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, as before. Curriculum updates for highly technology-exposed occupations yield 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% (cohort 2), 4.8% (cohort 3), 5.8% (cohort 4), and 6.3% (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 entrants trained in low technology-exposed occupations reach at most 2.5% (cohort 4) and stabilize at 2.1% 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 $p = 0.00$. Appendix Figure C4 shows these daily wage effects translate to higher annual earnings, with substantially larger effects for more technology-exposed occupations.

One 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, as illustrated by the dashed arrow in Figure 1. We address this concern by controlling

for each occupation's technology exposure over time, computed linking the *pre-update* curriculum text to the patent flow relevant for each cohort. The inclusion of this control variable holds constant the technology-driven demand shifts an occupation would have experienced absent a curriculum change. Appendix Figure C5 shows that our results are unaffected.

This evidence suggests that technology is a key mechanism underlying entrants' wage returns from skill updates: updates spurred by advancing technology impart larger and longer-lasting labor market advantages than those driven by other factors. This pattern is consistent with the expertise mechanism in Autor et al. (2026), who show that new work within occupations—particularly technology-linked new work—commands wage premia because the specialized expertise it requires is initially scarce. Our results add causal evidence to this account, showing that curriculum adaptation produces this novel expertise and raises the wages of workers trained in it.

A complementary explanation may be that updated technology-related skills enable or induce complementary capital investments which in turn raise the marginal product of workers with complementary skills. Two additional findings support this channel. Using Qualification and Career Survey data, Appendix C.1 shows that curriculum updates increase on-the-job use of computer technology among vocationally trained workers, but only for highly technology-exposed occupations (Appendix Table C1). Appendix E further shows that firms increase capital investments when exposed to updated vocational training, consistent with enhanced capital-skill complementarity.

Worker mobility. Next, we examine whether these labor market advantages accrue from differences in entrants' early career paths, using occupation, industry, and firm mobility as outcomes in equation (3).

Figure 12 displays mobility estimates relative to each entrant's apprenticeship position: that is, we consider whether the entrant has moved out of the 4-digit occupation, the 3-digit industry, or the firm where they did their apprenticeship.[37]

The mobility estimates reveal a distinct pattern. In the pre-update period, entrants trained in updating occupations are more likely to leave their training occupation, industry, and firm than comparable entrants 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 stabilize, while occupational mobility declines

[37] Results are similar when considering year-on-year mobility, i.e. relative to the occupation, industry, and firm of the past year.

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% (Table 6). 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 entrant wages. Eckardt (2026) shows that occupational mismatch causes an average wage penalty of 14% for German vocationally trained workers, reflecting the non-transferability of occupation-specific human capital across fields. By better aligning skill supply with current occupational demands (Section 3.2 and Appendix B.3), curriculum updates reduce the share of entrants ending up outside their training field— entrants 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% wage penalty for occupational mismatch yields an implied wage gain of 0.7 percentage points, compared to our 4.1% estimated wage return.

The role of firms. Firms enter our setting in two distinct roles: the employer an entrant joins after training, and the training firm where they completed their apprenticeship. We consider each in turn.

Employers. After the curriculum update, employer switching stabilizes (Figure 12), but new-skilled entrants increasingly sort into higher-paying firms post training. Panel A of Figure 13 shows that entrants trained under updated curricula work at firms with somewhat higher pay premia: employer AKM fixed effects increase by up to 1 log point for cohort 4. This raises the question of how much of the overall wage return operates through between-firm sorting versus within-firm skill pricing. Panel B of Figure 13 therefore presents wage estimates where we deduct employer AKM fixed effects from individual wages, along with the baseline results from Figure 10. Substantial wage returns remain when netting out employer pay premia: by cohort 5, new-skilled entrants earn approximately 3.1% higher wages even within firms with similar pay premia, indicating that the majority of wage gains reflect updated skills rather than sorting to higher-paying employers.

Training firms. Turning to the firms where entrants acquired their skills, Figure 14 examines whether wage returns vary by training firm size (total training firm employment at end of apprenticeship, median split), separately for low- and high-technology exposed updates. Within both exposure groups, workers trained in larger firms tend to experience somewhat larger wage gains for later cohorts, consistent with larger firms implementing updated cur-

ricula more effectively. This pattern also argues against the possibility that large firms were informally teaching new curriculum content ahead of the formal update: had they done so, the update would represent less of a novelty for their trainees, predicting smaller rather than larger returns. The technology exposure margin dominates in either case: high-exposure updates generate sizable wage returns regardless of training firm size, while low-exposure updates yield smaller returns. What workers are trained in thus matters more than where they are trained— the content of updated curricula, not the size of the training firm, is the primary driver of wage gains.

Robustness checks. Our baseline specification averages wages over the first five post-training years. This means that pre-update entrant cohorts partly earn their wages during years when new-skilled cohorts have already entered the labor market, raising a potential spillover concern which may impact the estimates for $c < 0$. To address this, we estimate the model separately by entrants' potential work experience. Appendix Figures C6 and C7 show that results hold at each experience level, overall and separately by technology exposure, and that wage returns tend to grow with post-training experience as expected.

We perform several additional robustness checks. First, Appendix Figure C8 shows that results are virtually identical when excluding from the control group the most common destination occupations of workers trained in the treated occupation (defined as occupations accounting for at least 10% of these workers' career employment, panel A), or occupations within the same two-digit occupation (panel B), mitigating concerns about SUTVA violations. Results are similarly robust to excluding the single or two largest destination occupations of each treated training occupation. Second, panel A of Appendix Figure C9 shows that wage effects are not driven by subsequent educational upgrading by new-skilled entrants: 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.[38] Panel B of this figure shows that our results are also robust to controlling for workers' high school type, as expected given that curriculum updates do not alter trainees' educational composition (Appendix D).

[38] Longer-horizon estimates show some small positive effects on university upgrading. On the whole, German vocationally trained workers are not very likely to pursue further full-time education: in our sample, 2.7% obtain a university degree within 5 years post graduation, and 11% do so at some point over their entire careers.

To sum up, skill updates thus provide labor market entrants with advantages through higher wages, coupled with increased occupational retention. Wage gains largely reflect within-firm returns to updated skills, and concentrate among updates with high technology exposure. These findings suggest that within-occupation skill supply adjustments play an important role in reinstating workers' expertise as skill demands evolve.

4.3 Do curriculum updates induce skill obsolescence for old-skilled occupational incumbents?

Having established that new-skilled entrants benefit from curriculum updates, we now turn to a separate analysis studying how old-skilled incumbents are affected. Curriculum updates bring an inflow of new-skilled entrants who compete with incumbents for jobs in the same occupation and are better matched to current skill demands. The complementary capital investments these updates induce further shift production technology further toward new skills. Both channels may reduce the returns to the incumbents' skill bundle, and we interpret declining incumbent wages as evidence of skill obsolescence.

Empirical approach. We construct a sample of occupational incumbents, defined as vocationally trained workers employed full-time in the same occupation for at least five consecutive years before that occupation received a curriculum update. Because incumbents are already in the labor market before the curriculum update—unlike entrants, for whom pre-treatment outcomes do not exist—we can follow individuals over time and exploit within-worker variation. We estimate

$$Y_{ijte} = \sum_{\substack{\tau=-5 \\ \tau\neq-1}}^{5} \beta_\tau \text{Update}_{je} \times I_{\tau e} + \delta_{ie} + \gamma_{te} + \varepsilon_{ijte} \ , \tag{4}$$

where τ is event time such that $\tau = 0$ is the year of the curriculum update and $I_{\tau e}$ the corresponding event-time indicator.[39] We restrict the estimation window to $\tau \in [-5, 5]$, and the reference period $\tau = -1$ is omitted. Y_{ijte} is an outcome for incumbent i employed in occupation j in calendar year t within event e. δ_{ie} captures individual by event fixed effects, and γ_{te} calendar year by event fixed effects. We stack observations for different

[39] Because this design follows individual incumbents rather than comparing successive cohorts, the relevant dimension is calendar time relative to the update, not training cohort.

events, interact all controls with event dummies, and cluster standard errors at the level of treatment (occupation by event).

Update_{je} is a treatment dummy indicating whether occupation j is the updating occupation in event e. This separates our treatment group (incumbents employed in occupations with curriculum updates) from our control group (incumbents employed in occupations without curriculum updates). All treated incumbents are exposed to curriculum updates in their employment occupation from $\tau = 0$ onward.

We estimate the regression separately for incumbent workers of different age groups (with age measured in $\tau = 0$): 50–59, 40–49, and 30–39 years old. Since older workers are least likely to upgrade their skills on the job, the losses experienced by the oldest workers most closely reflect pure skill price changes (Heckman et al., 1998; Bowlus et al., 2023). For each event, we draw all treated incumbents and an equally large random sample of control incumbents in the same broad occupation group (manufacturing or service)— with a minimum of 100 control incumbents when fewer than 100 treated incumbents are observed. As before, we drop a small number of events with fewer than 20 treated workers. This results in a sample of 710,926 unique incumbents in the treated group and 596,398 in the control group (who can be used as controls in multiple events) and 419 events. As before, control group workers are weighted by $1 \times N_{\text{treat}}/N_{\text{control}}$, with N_{treat} the number of treated observations per event and N_{control} the number of control observations per event.

The parameters of interest are β_τ, which give the effect of exposure to trainees with new skills on a range of incumbent worker outcomes: log daily wages, log annual earnings, and job mobility. For log wages, for example, we expect negative post-treatment estimates ($\beta_{\tau \geq 0} < 0$) if competition from new-skilled workers reduces the returns to incumbents' skills, indicating skill obsolescence, or positive post-treatment estimates ($\beta_{\tau \geq 0} > 0$) if incumbents benefit from new-skilled workers via, for example, learning or q-complementarity.

As for entrants, identification exploits the discrete timing of curriculum updates. Consistent with effects arising from the discrete timing of updates rather than gradual demand shifts, results are unchanged when controlling for each occupation's evolving technology exposure.

Descriptives. Table 7 shows descriptives of occupational incumbents. On average, incumbents are 41 years old, 43% are female, and they earn around 91 euros daily— 37% more than the early career workers we considered earlier. Unsurprisingly, incumbents have lower job mobility than early career workers: their year-to-year probabilities of switching occupations, industries, and firms are 12%, 11%, and 16%, respectively, compared with 19%, 20%, and

30% for early career workers.[40]

Findings. Panel A of Figure 15 shows that curriculum updates negatively affect wages for older occupational incumbents (ages 40 and older, but especially ages 50–59), consistent with skill obsolescence. These wage losses cumulate over time: after five years, daily wages fall by 1.9% for incumbents aged 40–49, and 3.4% for incumbents aged 50–59. For the youngest incumbents (ages 30–39) wage losses are very small and not statistically significant, consistent with a higher incentive or ability to adjust. Additional evidence presented in Appendix F suggests that firms do not broadly offset this skill obsolescence through retraining: Appendix Figure F1 shows that curriculum updates somewhat increase employer-paid training in exposed compared to non-exposed firms only among firms that themselves train apprentices in the updated occupation, with no training response among other firms employing incumbent workers in occupations whose curricula were updated.

Panel B of Figure 15 shows similar results for log annual earnings, implying that incumbents do not work fewer days a year in response to the entrance of new-skilled workers.

Appendix Figure C11 shows that our treatment effects are robust to controlling for occupations' technology exposure based on the pre-update curriculum. However, we cannot rule out that they simply reflect a continuation of incumbents' wages being on a negative trend: occupations with updates experience experience more technological change, reducing incumbents' wages.

In contrast to new-skilled entrants, incumbents— especially the younger ones— are *more* likely to switch 4-digit occupations or 3-digit industries, as shown in panels A and B of Figure 16. (Results are robust to considering more aggregate occupation and industry classifications.) This suggests that, while new-skilled entrants have skills relevant for the occupation they were trained in, reducing their occupation switching, younger incumbents lack the expertise currently relevant for their occupation and respond by switching to other jobs. We also find that incumbents, especially younger ones, are more likely to switch firms, shown in panel C of Figure 16. These findings are consistent with Janssen and Mohrenweiser (2018), who study the effect of a single curriculum update involving CNC skills on incumbents, finding wage losses coupled with increased occupational mobility (and only small and transitory non-employment effects).

The firm sorting pattern for incumbents mirrors that for entrants, with opposite sign.

[40] Appendix Table C3 shows descriptives for the stacked sample of incumbents, and Appendix Table C4 shows descriptives for the stacked sample separately by age group.

While new-skilled entrants move to higher-paying employers, incumbents move in the opposite direction: panel A of Figure 17 shows declining employer AKM fixed effects for all age groups, with smaller effects for the youngest age group. Panel B shows wage effects controlling for AKM firm fixed effects. As with entrants, firm sorting explains only part of the outcome: controlling for firm pay premia slightly attenuates the wage decline—more so for the older two groups—but substantial within-firm losses remain for both older age groups. The dominant channel is thus a within-firm deterioration in the returns to incumbent skills, not displacement to lower-paying employers.

These results provide causal evidence for the skill obsolescence pattern that Deming and Noray (2020) documents cross-sectionally for STEM workers—flattening age-earnings profiles and higher job switching out of faster-changing educational fields—and suggest the inflow of new-skilled entrant cohorts as one mechanism driving these outcomes. Two reinforcing channels may operate. First, new-skilled entrants compete with incumbents for jobs in the same occupation, and are better matched to current occupational skill demands. This erodes the value of incumbents' expertise—the mirror image of the expertise reinstatement we document for entrants. Second, the complementary capital investments that curriculum updates induce shift production technology further toward new skills, reducing the returns to the incumbents' skill bundle. The fact that incumbent wage losses persist after controlling for occupations' technology exposure indicates that these effects are driven by the discrete curriculum update rather than by gradual technology-driven demand shifts.

5 Conclusion

Advancing technology reshapes skill demands: can changes in educational content enable workers to adapt? We study this question using vocationally trained workers in Germany, a large population of non-college educated workers concentrated in middle- and low-paid occupations, many of which are highly exposed to technology. Leveraging a novel database of legally binding training curricula spanning 1971–2021 linked to administrative employer-employee data, we trace a complete causal chain from technological change to curriculum content to worker outcomes.

We establish four main findings. First, technological advances drive curriculum updates: occupations more exposed to digital technology update their training content more frequently and more rapidly. Second, these updates bring about substantial skill evolution—

curricula shift toward less routine-intensive tasks, predominantly through the emergence of new skills rather than the removal of old ones, highlighting that workers acquire entirely new competences. This within-occupation adjustment margin is quantitatively important: curriculum updates account for two-thirds of the aggregate decline in routine task content of vocational occupational skill supply over this period, paralleling previous findings that within-occupation task change dominates aggregate skill demand shifts.

Third, curriculum updates generate significant returns for 'new-skilled' workers. Labor market entrants trained under updated curricula earn up to 4.1% higher wages and remain employed in their trained occupation at higher rates than those trained under outdated curricula in the same occupation, relative to entrants in occupations without curriculum updates. These wage gains reflect absolute improvements—faster wage growth for new-skilled workers, not deterioration among comparison cohorts— and concentrate among curriculum updates with high technology exposure, indicating that aligning training content with technological change keeps workers' expertise labor-market relevant.

Fourth, skill updates create winners and losers. Older incumbent workers (ages 50–59) experience wage declines of up to 3.4% when new-skilled workers enter their occupation, consistent with skill obsolescence. Younger incumbents do not experience significant wage declines but respond by switching occupations. Firms exposed to workers trained in updated curricula increase capital investments, especially for technology-exposed occupations, consistent with enhanced capital-skill complementarity for workers with new skills.

Our findings demonstrate that educational content adaptation—not just rising educational attainment—matters for reinstating the value of labor as technology advances because it provides workers with scarce, novel expertise. This holds particular importance for non-college post-secondary education, which equips workers for a wide range of middle-class occupations. Our results also highlight the need to retrain occupational incumbents, who fall behind as their occupations' skill demands evolve: employer-provided training rises only weakly and among firms that train apprentices in the updated occupation themselves, not more broadly.

Several questions raised by our analysis merit further study. First, curriculum updates in Germany result from negotiations among employer organizations, labor unions, and the Federal Institute for Vocational Education and Training (BIBB). Recent work suggests that employer involvement may help keep skills labor-market relevant (Katz et al., 2022; Dillon et al., 2025), and coordination through legally binding curricula may raise firms' willingness to invest in training that individual employers, fearing poaching, might otherwise underpro-

vide. Consistent with this channel, we find that apprenticeship positions increase following curriculum updates. Benefits for workers may be further strengthened by the active role of labor unions and BIBB, who emphasize that curriculum content should be general rather than firm-specific. Understanding how institutional arrangements shape the speed and nature of educational content adaptation represents a promising avenue for future research.

Finally, our setting spans five decades in which digital technology has been the dominant source of new skill demand, shifting training content toward non-routine tasks. Artificial Intelligence, unlike earlier waves of digital technology, is increasingly capable of performing such tasks—whether and how curricula will adapt to this shift is an open question our data cannot yet answer. AI may also change the cost of acquiring new expertise, or require changes to how training is delivered and how competence is demonstrated—dimensions our curriculum data also capture and that future work could exploit.

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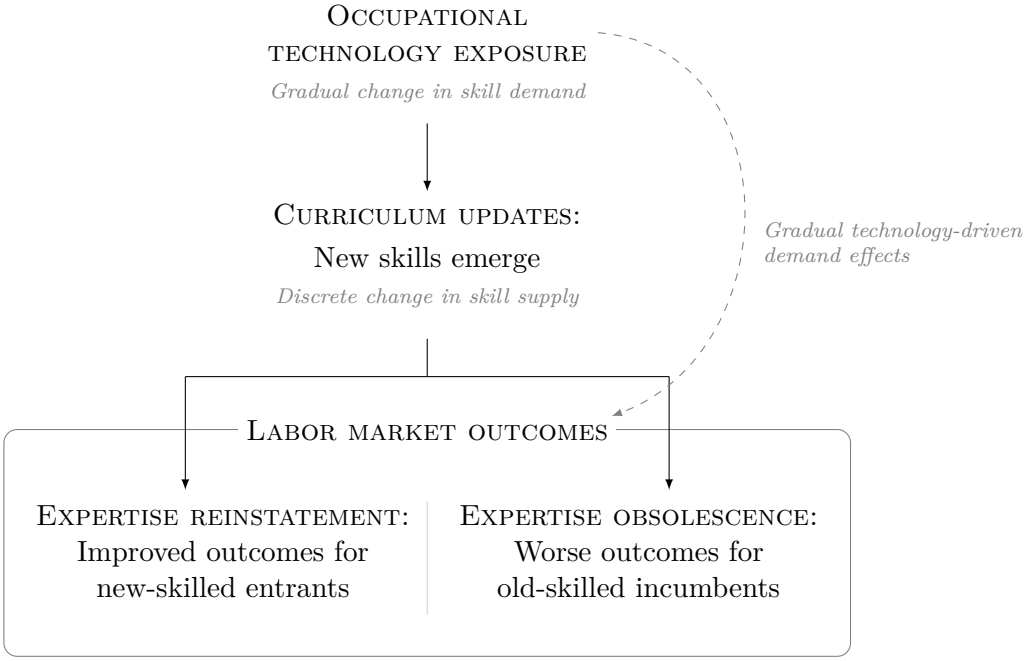
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Figures

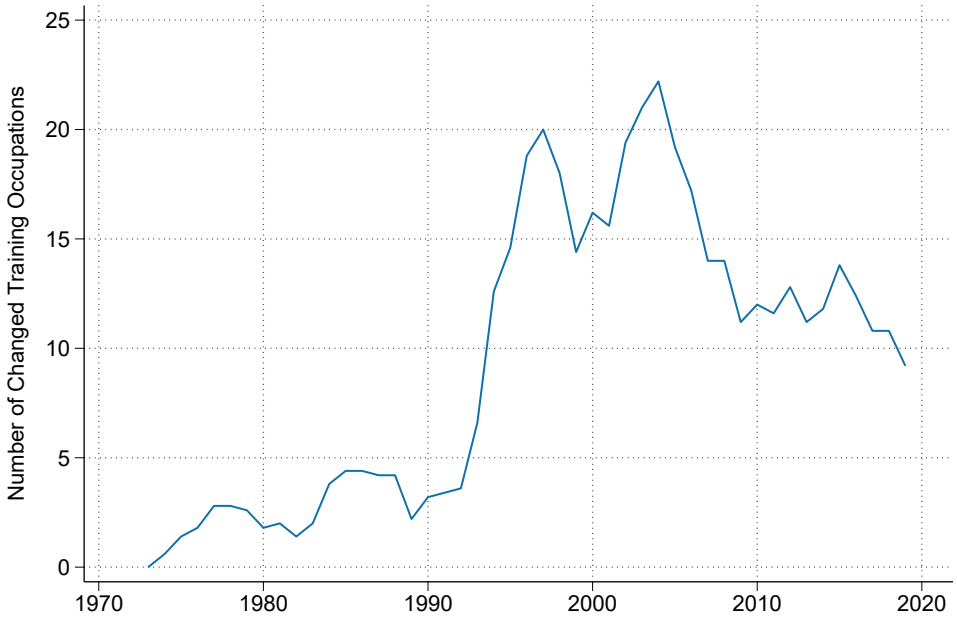
Figure 1: Causal Chain from Technological Change to Worker Outcomes: The Skill Supply Channel



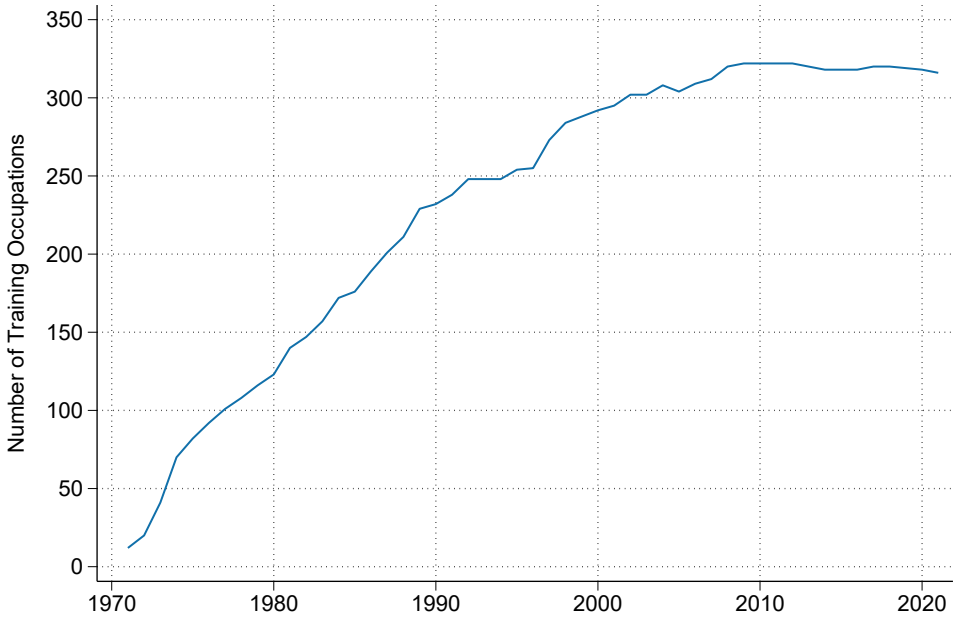
Solid arrows show the causal chain established in this paper. The dashed arrow represents gradual technology-driven occupational demand shifts that may affect worker outcomes independently of discrete curriculum updates; our identification exploits the discrete timing of updates to separate the two.

Figure 2: Curriculum Updates Over Time

A. Number of Curriculum Changes by Year



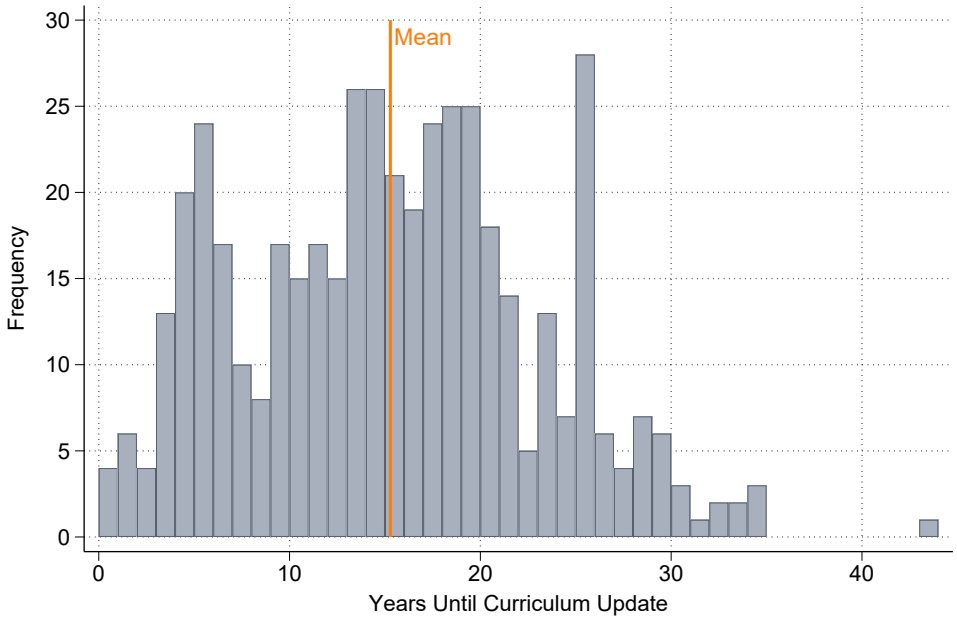
B. Number of Training Occupations with Observed Curriculum by Year



Panel A shows the 5-year moving average of the number of curriculum changes by year. Panel B shows the number of active training occupations in the national register after the introduction of the Vocational Training Act in 1969.

Figure 3: Years until Curriculum Update

A. Overall



B. By Broad Occupation Group

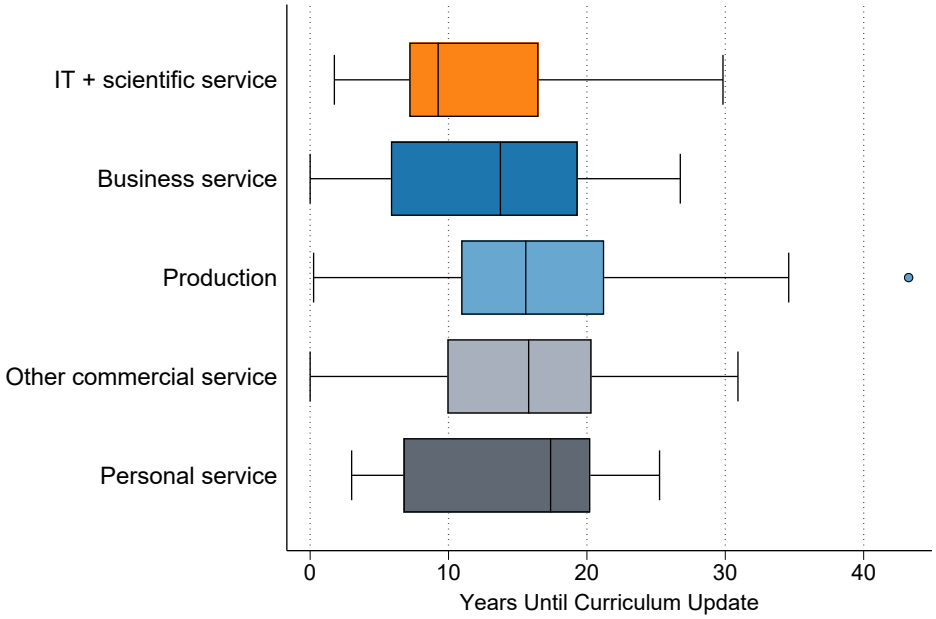


Figure shows the distribution of years until curriculum updates for initial training occupation observations ($N = 470$). Panel A shows the overall distribution across training occupations. Panel B shows a boxplot by broad occupation group. Vertical lines indicate the median; boxes reflect the interquartile range; and whiskers indicate the 10th and 90th percentiles.

Figure 4: Share of Breakthrough Patents by Technology Class

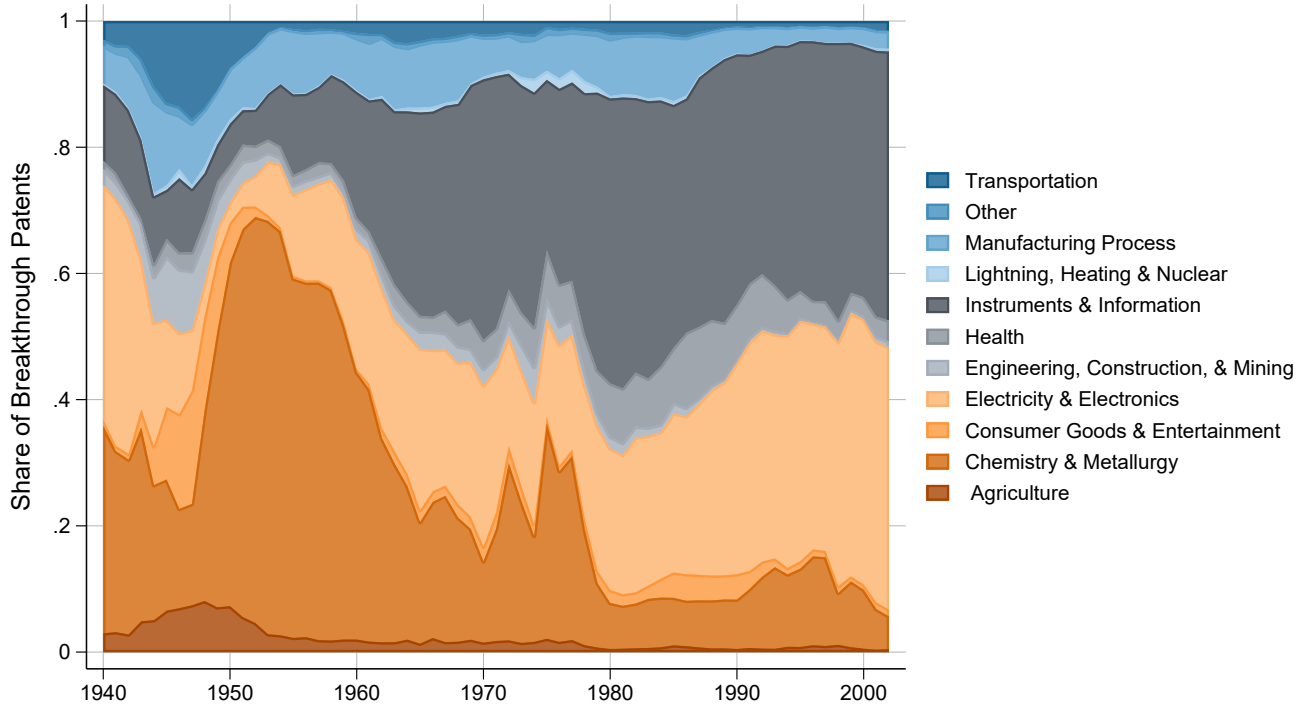
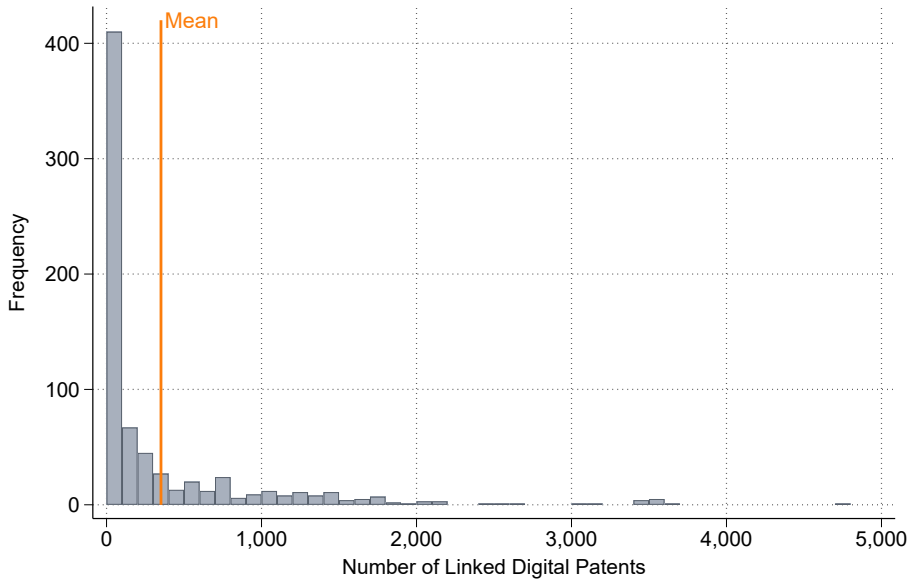


Figure shows the distribution of breakthrough patents across broad technology classes defined by Kelly et al. (2021). Over 1940–2002, we observe $N = 141,708$ breakthrough patents in Instruments & Information.

Figure 5: Digital Technology Exposure of Training Curricula

A. Overall



B. By Broad Occupation Group

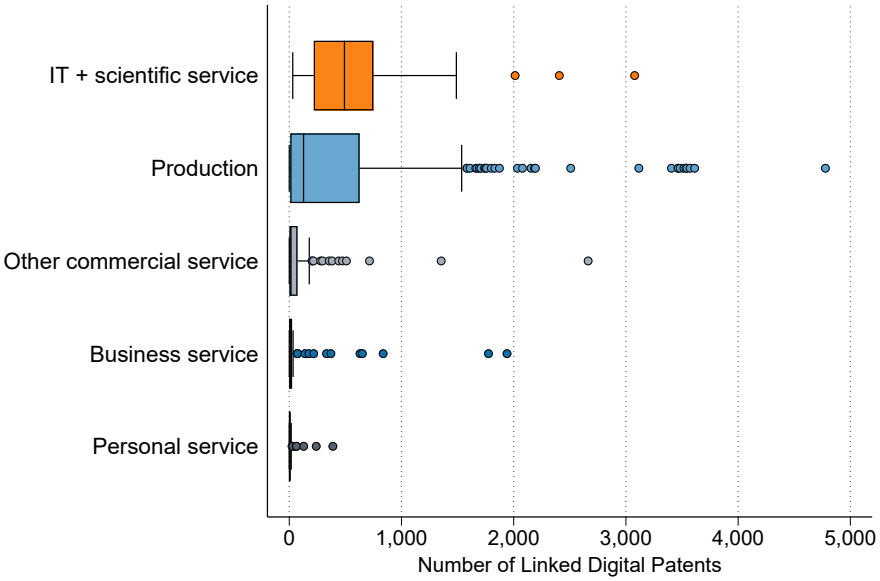


Figure shows the distribution of linked digital patent counts for initial training occupation observations ($N = 791$). Panel A shows the overall distribution across training occupations. Panel B shows a boxplot by broad occupation group. Vertical lines indicate the median; boxes reflect the interquartile range; and whiskers indicate the 10th and 90th percentiles.

Figure 6: Curriculum Survival Rates by Technology Exposure

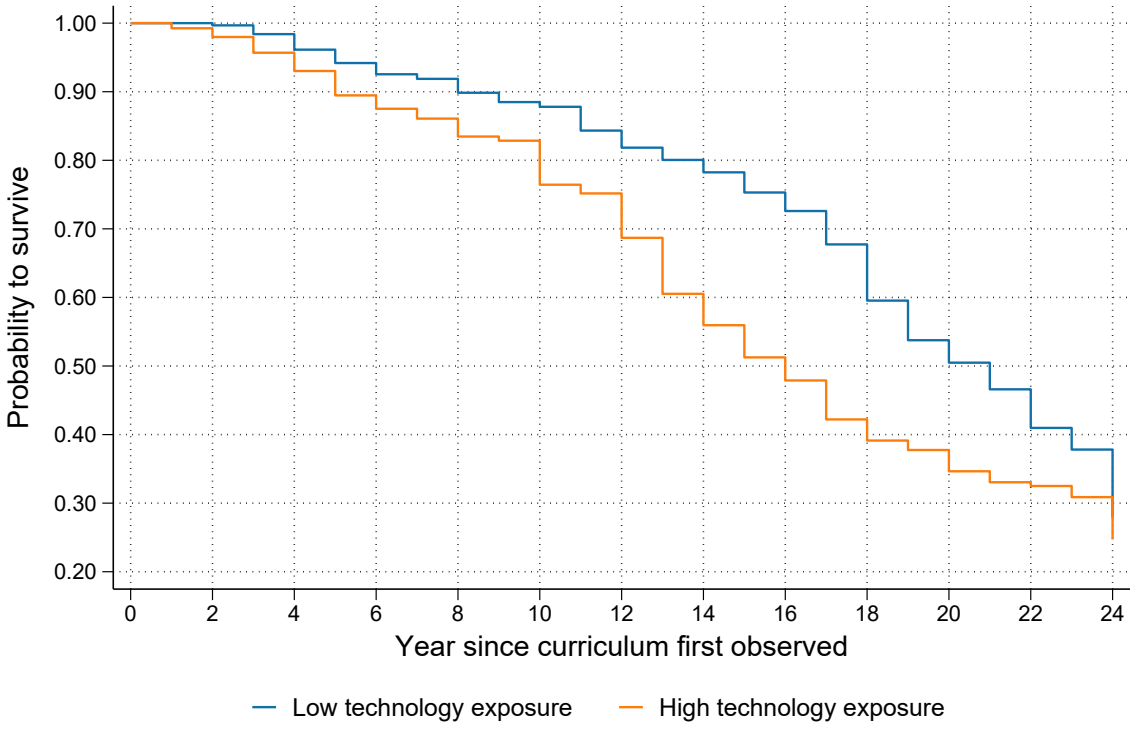


Figure shows Kaplan-Meier survival curves separately by technology exposure. Low technology exposure is below-median exposure; high technology exposure is at or above median exposure. Durations longer than 24 years are discarded due to small sample size.

Figure 7: Changes in Non-Routine Task Intensity in Updated Curricula, 1976–2021

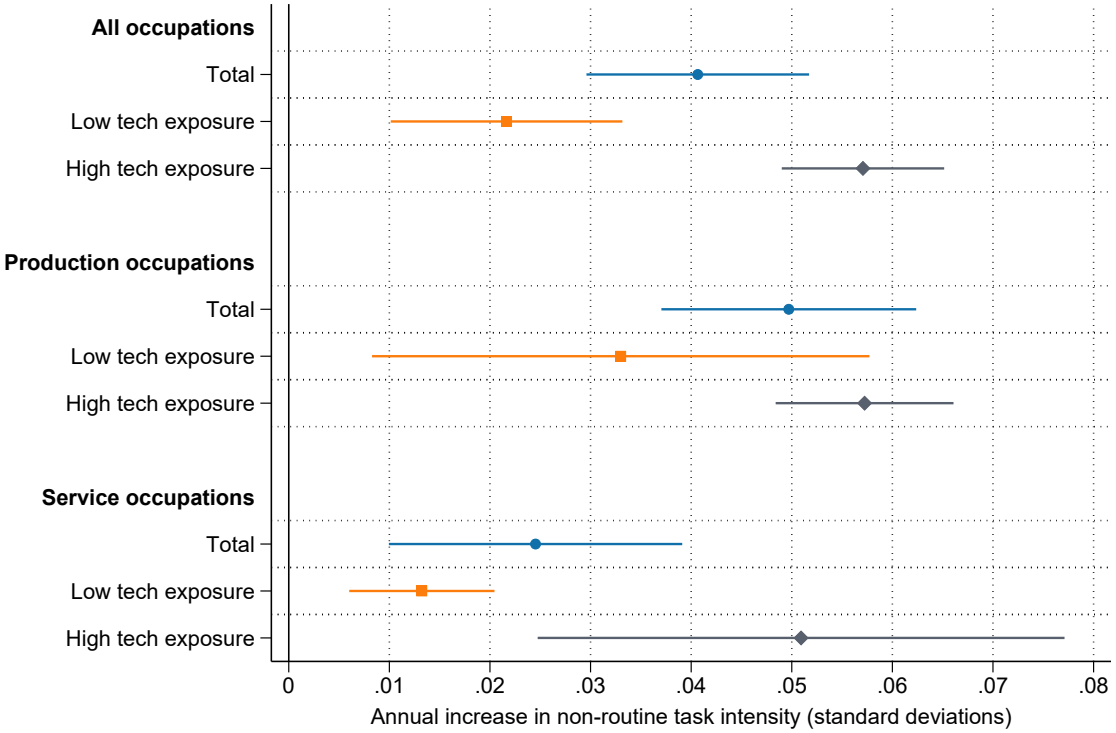


Figure reports coefficients on a linear timetrend, from a regression of non-routine task content in vocational training curricula (see equation (2)), for the subsample of curricula with updates over 1976–2021. Horizontal lines reflect 95% confidence intervals. High tech (low tech) defined as curricula with an initial digital technology exposure above (at or below) the median across all occupations.

Figure 8: Changes in Curriculum Non-Routine Task Intensity from Removed, Remaining, and Newly Added Words

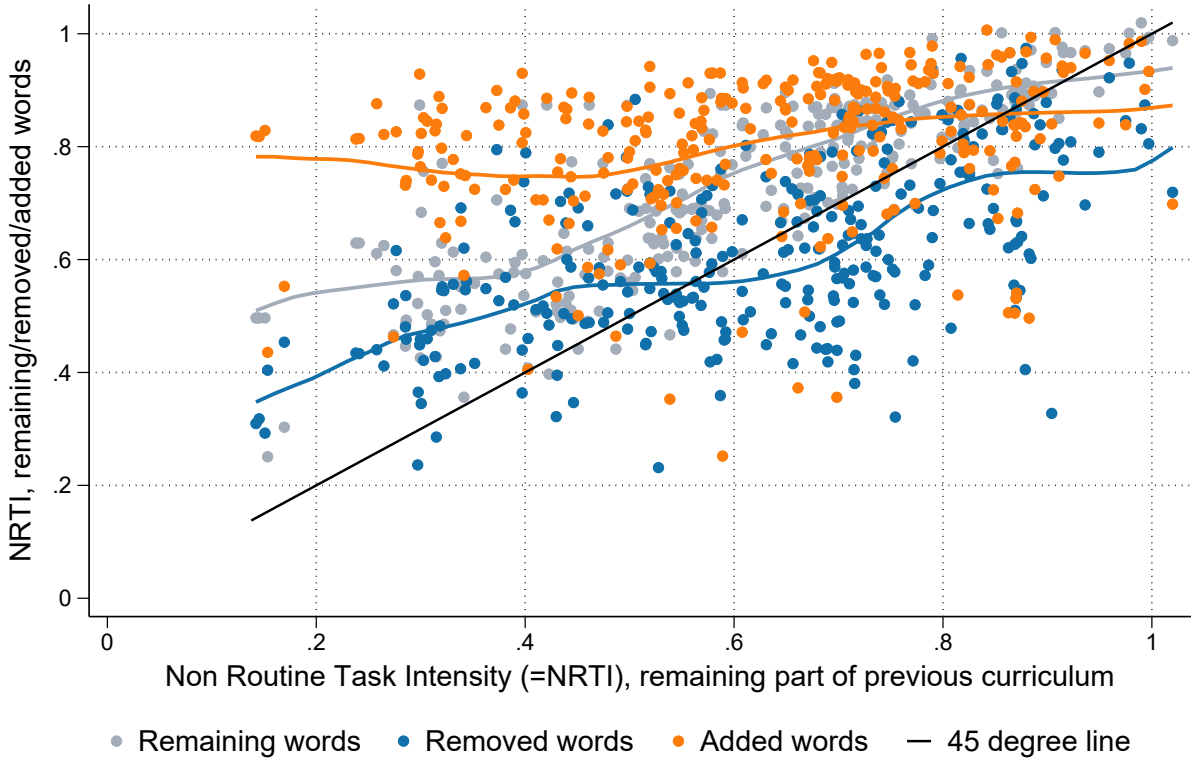


Figure presents the non-routine task intensity of new curriculum words plotted against remaining words in the previous curriculum. Fitted lines are local polynomials weighted by training occupation employment shares.

Figure 9: Distribution of Newly Added Words Relative to Removed Words Across Skill Categories

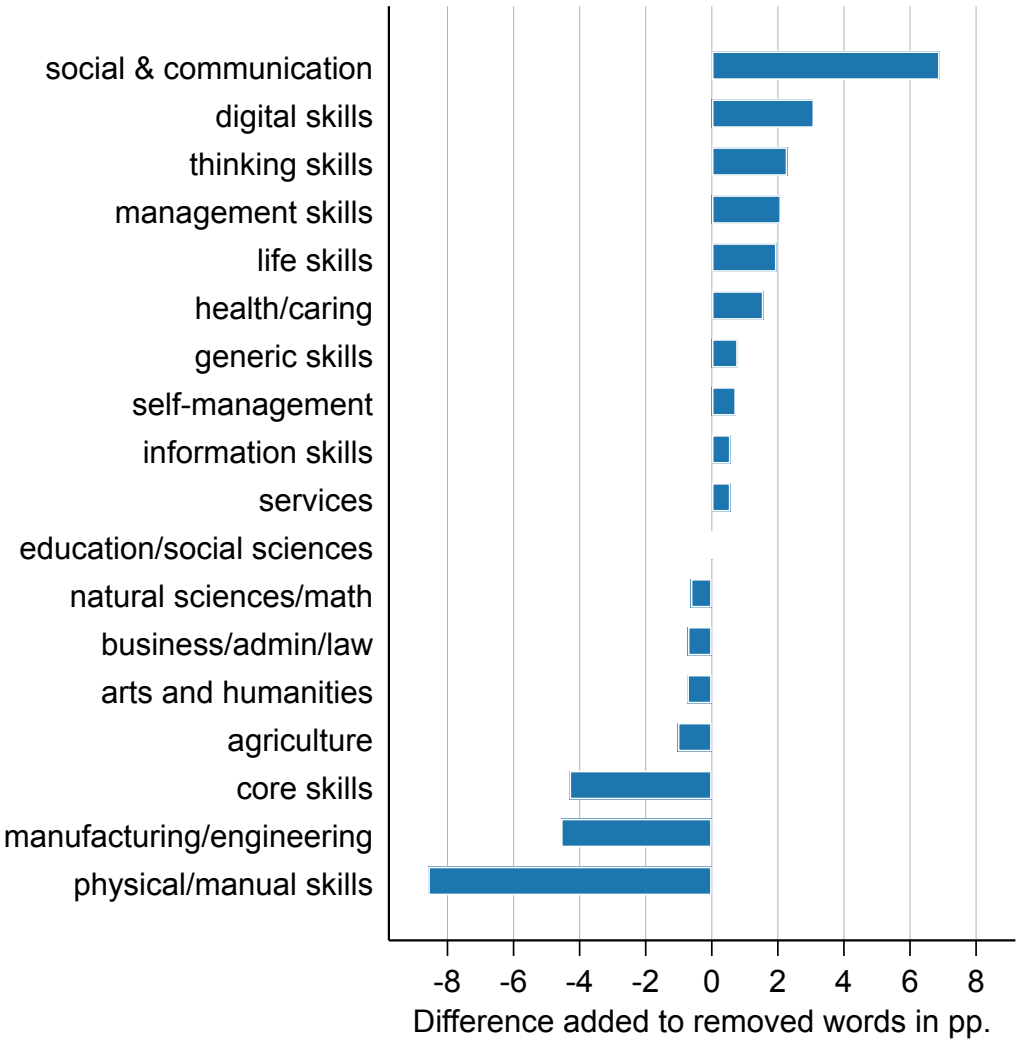
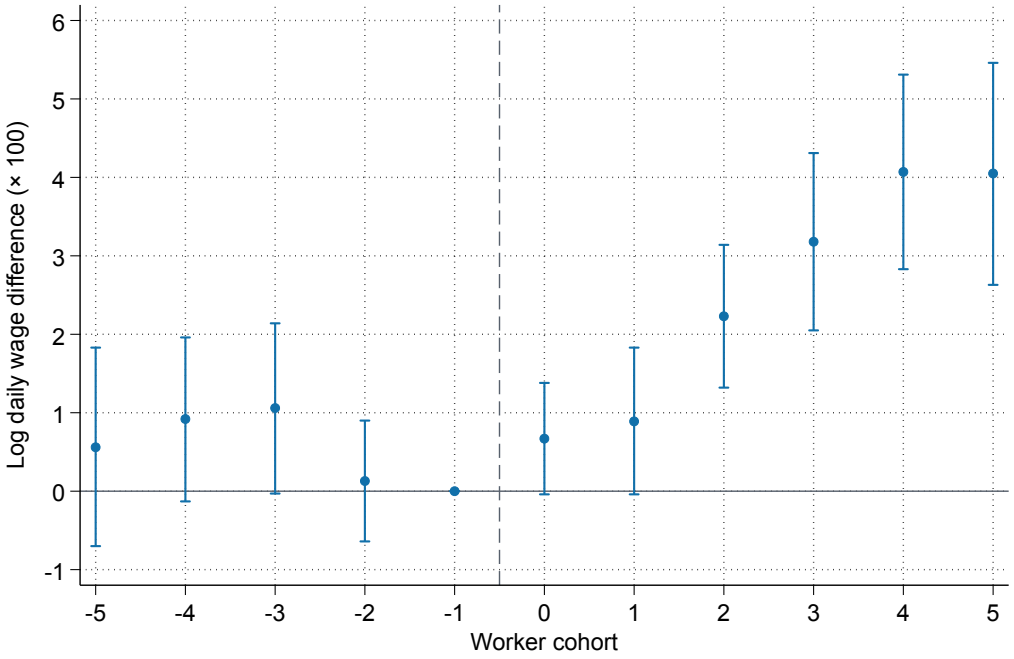


Figure presents the distribution of newly added words relative to the distribution of removed words in curriculum updates across ESCO skills categories. Appendix A.2 shows unabbreviated skill labels and descriptions. Bars sum to zero.

Figure 10: Entrant Wage and Earnings Impacts of Curriculum Updates

A. Log Daily Wage



B. Log Annual Earnings

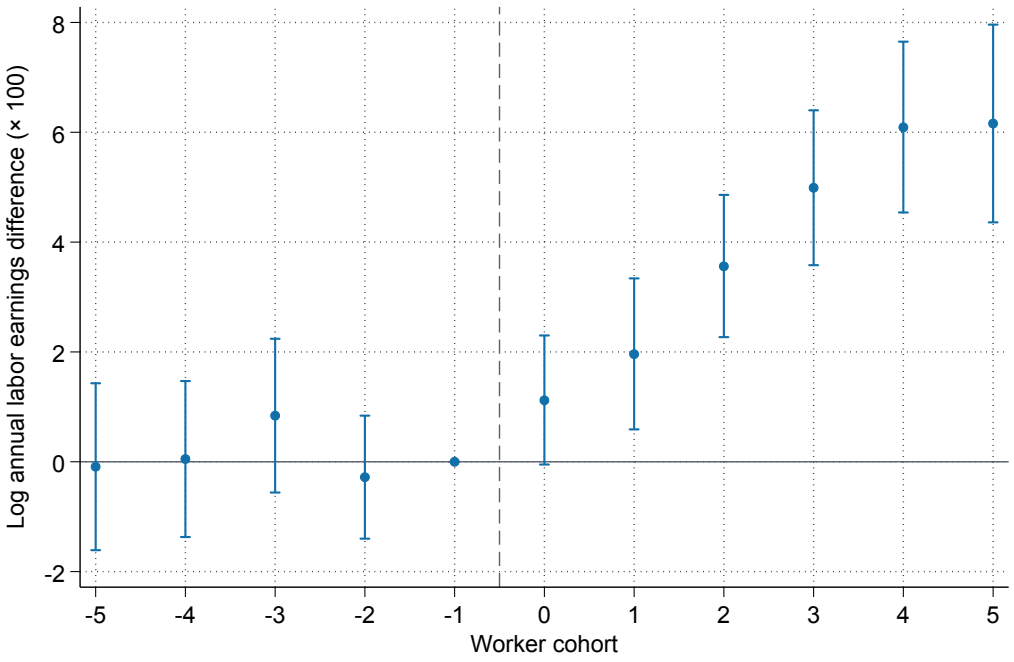
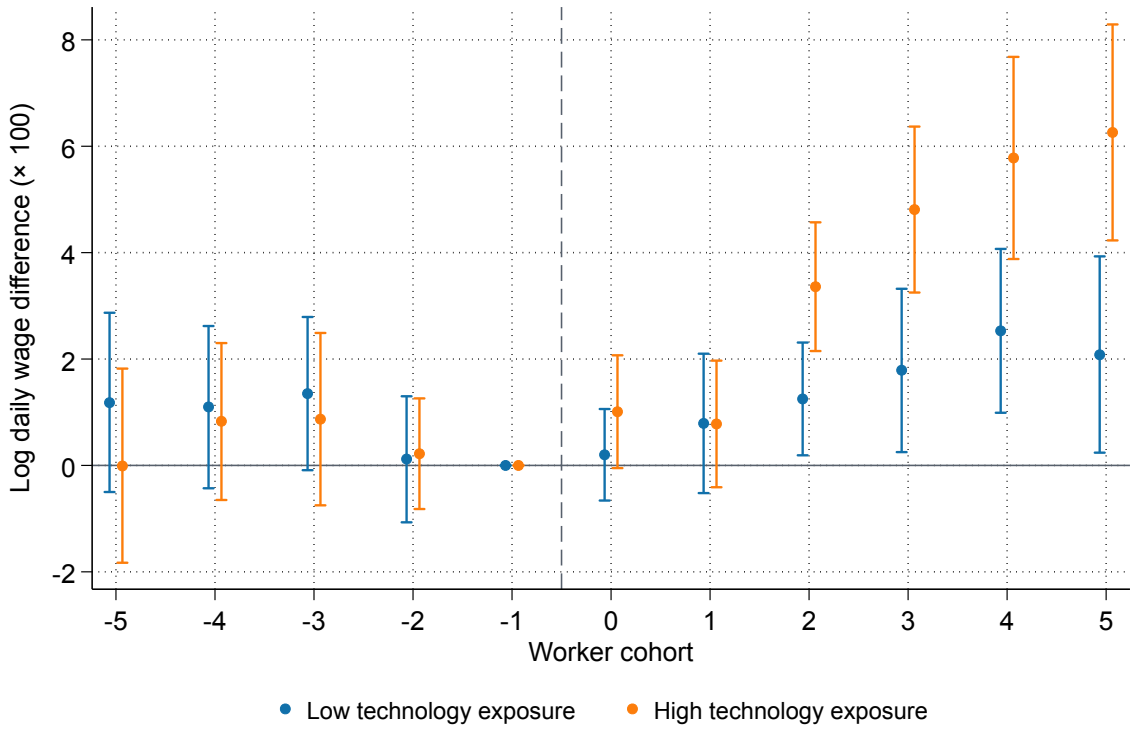


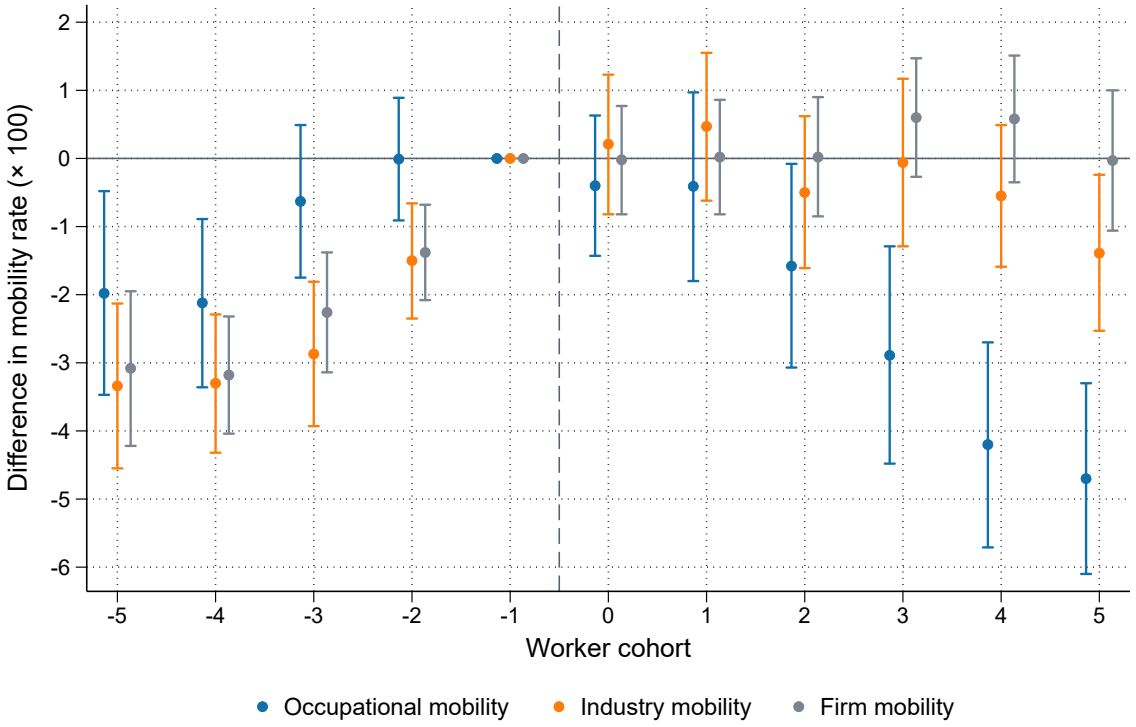
Figure reports stacked difference-in-differences estimates of equation (3), and 95% confidence intervals. Cohort 0 is the first cohort with the new curriculum; cohort -1 is the reference category. Individuals are included up to five years after graduation. Standard errors clustered at the level of occupation 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 11: Entrant Wage Impacts of Curriculum Updates by Technology Exposure



Stacked difference-in-differences estimates of equation (3), 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 $p = 0.00$.

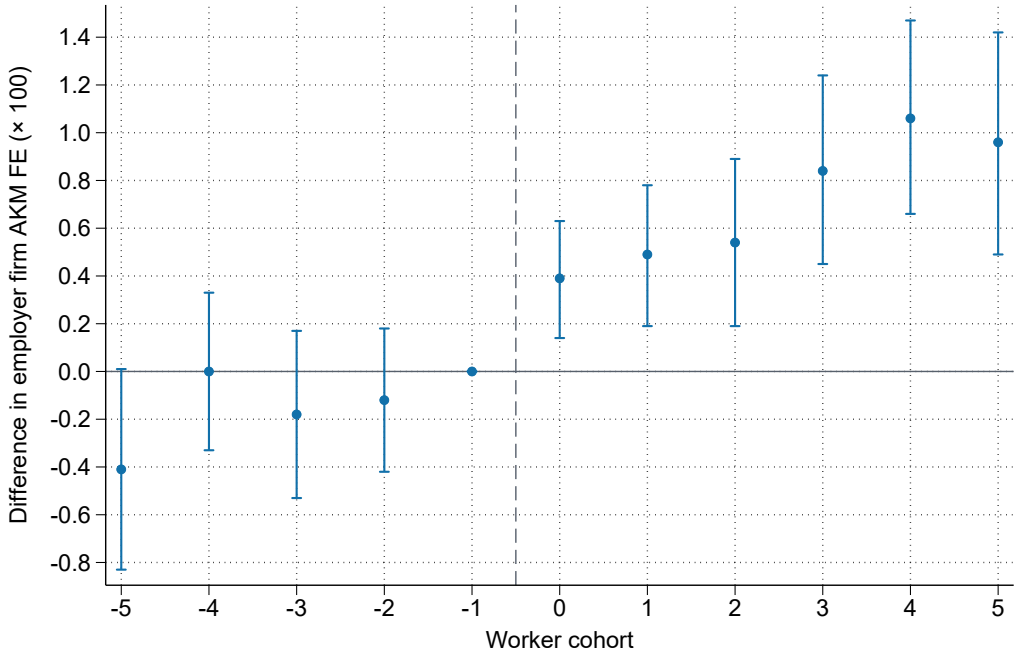
Figure 12: Impacts of Curriculum Updates on Entrant Mobility



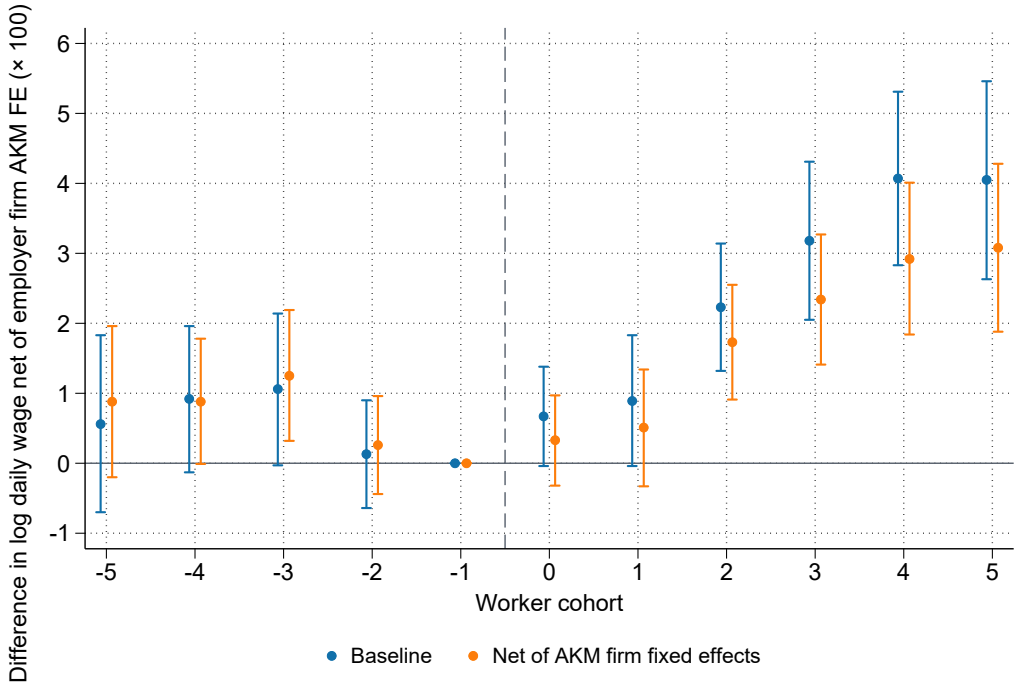
Stacked difference-in-differences estimates of equation (3), and 95% confidence intervals. Mobility is defined relative to the apprenticeship position. Cohort 0 is the first cohort with the new curriculum; cohort -1 is the reference category. Individuals are included up to five years after graduation. Standard errors clustered at the level of occupation by event. 357 events, $N = 9,012,391$.

Figure 13: Impacts of Curriculum Updates on Entrant Wages: The Role of Employer Firms

A. Employer Firms' AKM Fixed Effects

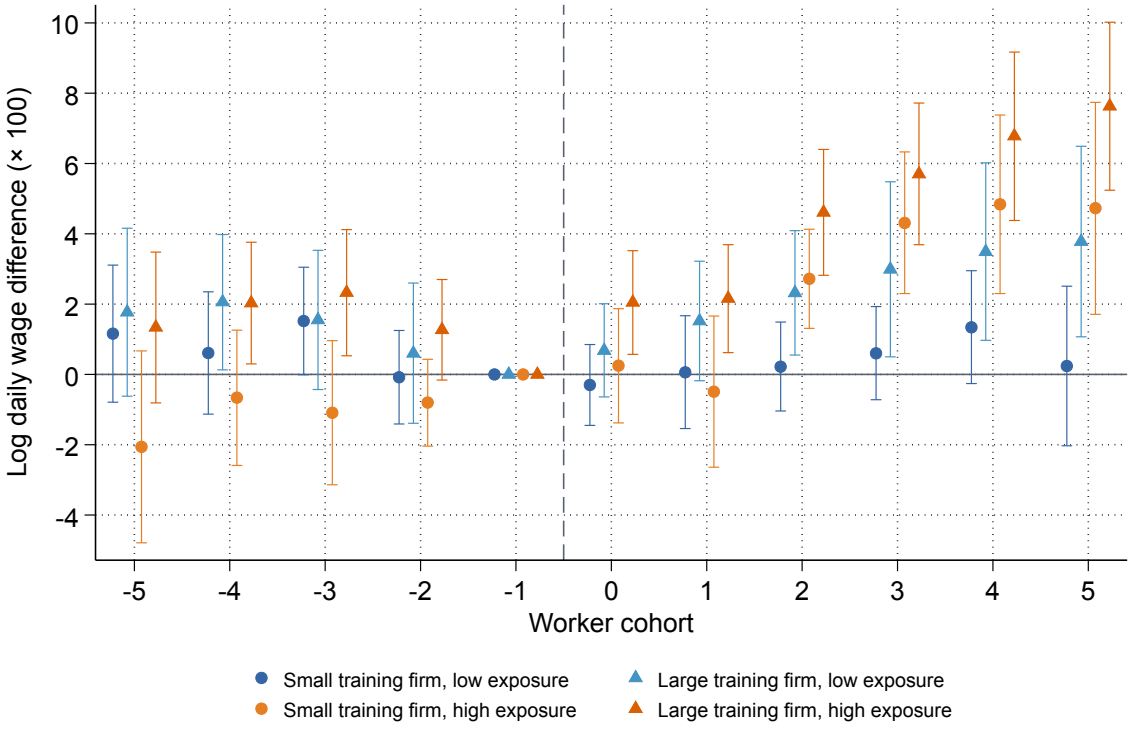


B. Daily Wages Net of Employer Firms' AKM Fixed Effects



Stacked difference-in-differences estimates of equation (3), 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. Panel B: the specification nets out AKM fixed effect of workers' employment firms (also constructed from log daily wages). Panel A: $N = 8,880,564$; Panel B: $N = 8,838,173$; 357 events for both panels.

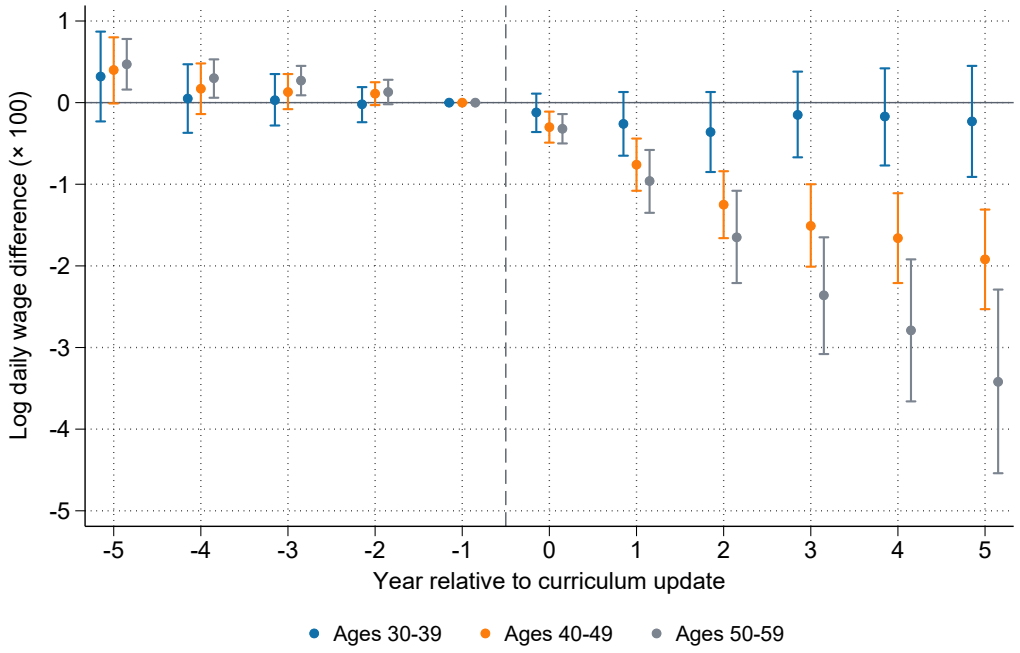
Figure 14: Impacts of Curriculum Updates on Entrant Wages: The Role of Training Firm Size



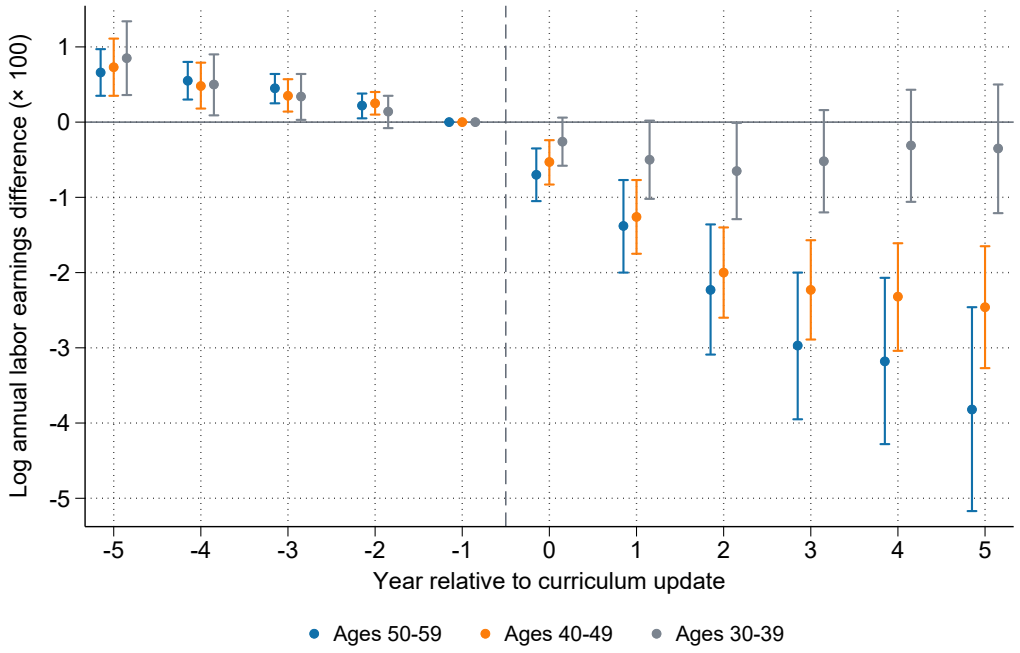
Stacked difference-in-differences estimates of equation (3), and 95% confidence intervals. Cohort 0 is the first cohort with the new curriculum; cohort -1 is the reference category. Individuals are included up to five years after graduation. Standard errors clustered at the level of occupation by event. 174 events for low exposure, 182 events for high exposure. $N^{\text{high}}_{\text{small}} = 2,118,153$; $N^{\text{high}}_{\text{large}} = 2,133,933$; $N^{\text{low}}_{\text{small}} = 2,668,486$; $N^{\text{low}}_{\text{large}} = 2,046,312$.

Figure 15: Wage and Earnings Impacts of Curriculum Updates for Occupational Incumbents

A. Log Daily Wage

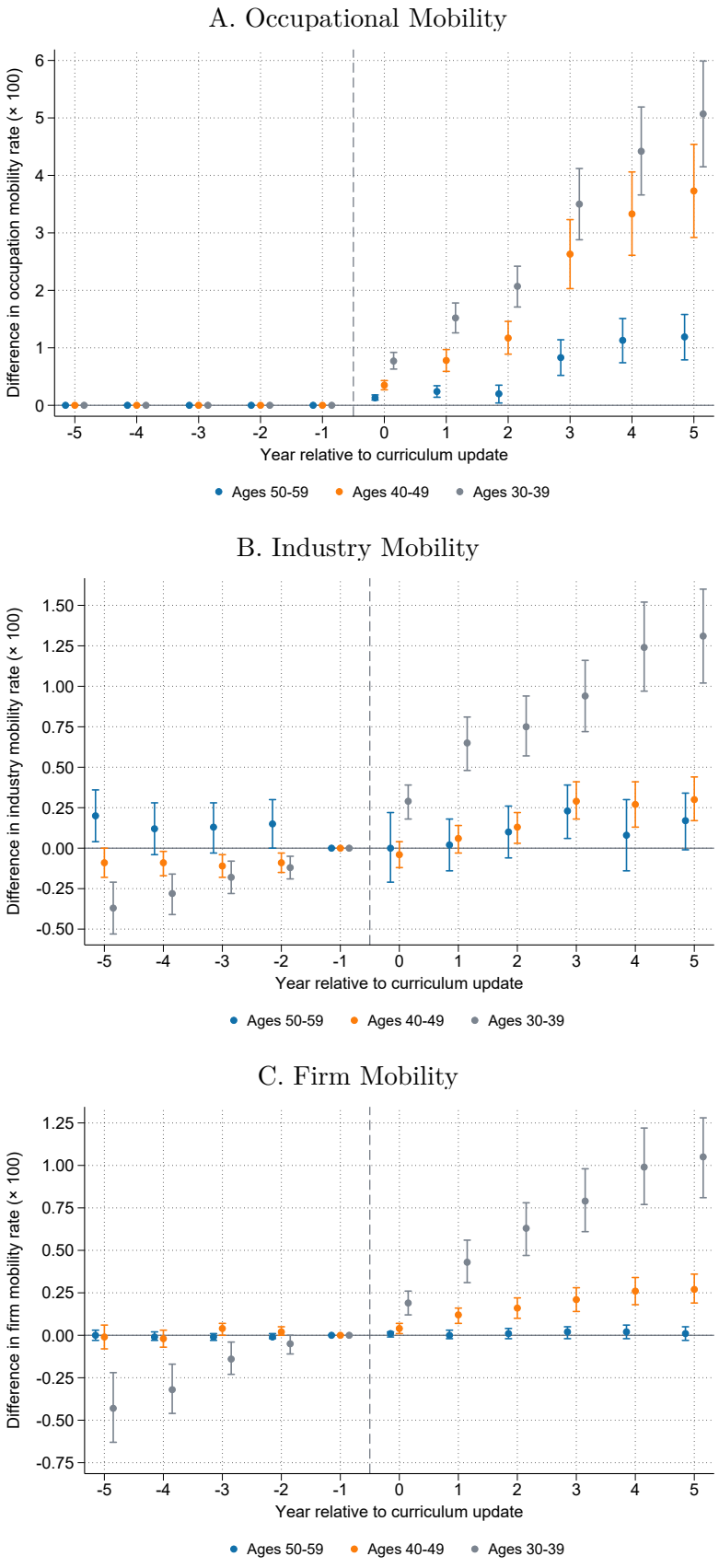


B. Log Annual Earnings



Stacked difference-in-differences estimates of equation (4), and 95% confidence intervals. Age measured in $t = 0$. Based on 419 curriculum update events for both panels. $N_{50-59} = 4,860,341$, $N_{40-49} = 7,504,989$, $N_{30-39} = 6,664,012$ for both panels. Panel A: A Wald test of the joint significance of the coefficients for $\tau < -1$ yields $p = 0.015$, $p = 0.010$, and $p = 0.003$ for ages 50–59, 40–49, and 30–59, respectively. Panel B: A Wald test of the joint significance of the coefficients for $\tau < -1$ yields $p = 0.000$, $p = 0.001$, and $p = 0.002$ for ages 50–59, 40–49, and 30–39, respectively.

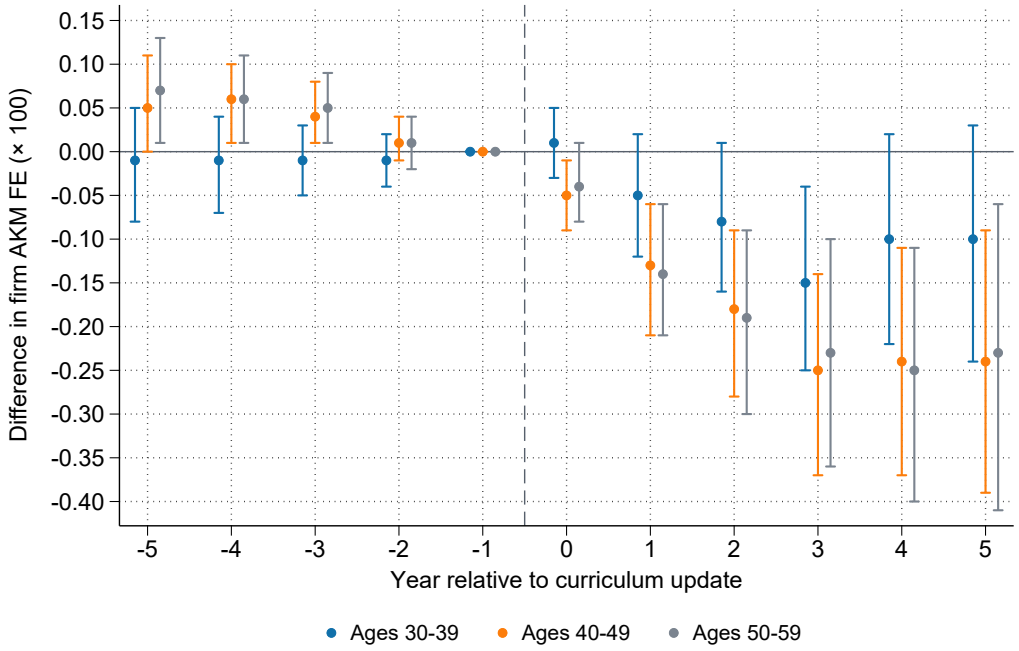
Figure 16: Job Mobility Impacts of Curriculum Updates for Occupational Incumbents



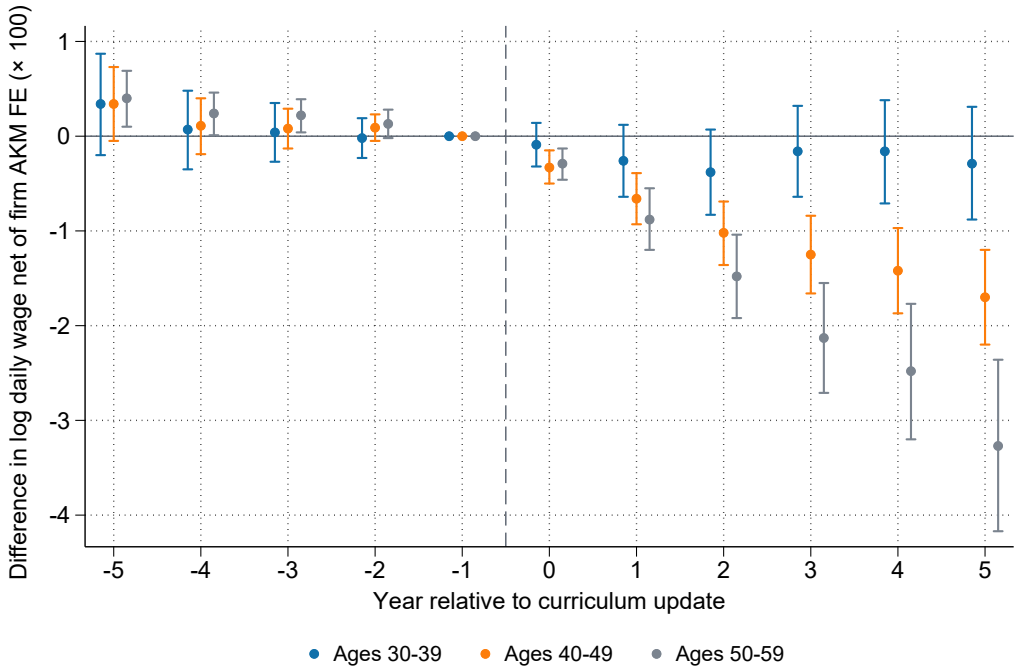
Stacked difference-in-differences estimates of equation (4), and 95% confidence intervals. Age measured in $t = 0$. Based on 419 curriculum update events for all panels. Panel A: $N_{50-59} = 2,665,873$, $N_{40-49} = 4,428,832$, $N_{30-39} = 3,911,246$; Panels B and C: $N_{50-59} = 4,725,374$, $N_{40-49} = 7,377,891$, $N_{30-39} = 6,529,453$. Panel A observations are lower because mobility is only estimated over the post-period (it is constant by construction for $t < 0$).

Figure 17: Impacts of Curriculum Updates on Incumbent Wages: The Role of Firms

A. Firms' AKM Fixed Effects



B. Daily Wages Net of Firms' AKM Fixed Effects



Stacked difference-in-differences estimates of equation (4), and 95% confidence intervals. Age measured in $t = 0$. Based on 419 curriculum update events for both panels. Panel A: $N_{50-59} = 4,686,166$, $N_{40-49} = 7,331,238$, $N_{30-39} = 6,494,318$. Panel B: $N_{50-59} = 4,682,662$, $N_{40-49} = 7,329,124$, $N_{30-39} = 6,491,187$.

Tables

Table 1: Largest Occupations with a Vocational Training Curriculum

	Avg. empl. share in %	Δ Empl. share in pp	Avg. real daily wage
Office clerks and secretaries	10.6	-6.2	101.6
Occupations in warehousing and logistics	4.3	0.3	82.3
Occupations in machine-building and -operating	3.4	-1.6	135.7
Sales occupations in retail trade	3.3	-2.5	70.6
Professional drivers (cargo trucks)	3.2	-0.9	87.4
Technical occupations in automotive industries	2.7	-1.5	100.2
Bankers	2.0	-0.6	142.5
Occupations in electrical engineering	1.9	-1.0	151.4
Management assistants in wholesale and foreign trade	1.4	-0.9	120.7
Occupations in metal constructing	1.4	-0.6	95.9

Source: SIAB. Average employment share: Average share of occupational regular full-time employment in total regular full-time employment across the years 1975–2021. Δ Employment share: Change in the share of occupational regular full-time employment in total regular full-time employment between 1975 and 2021 in percentage points. Average gross daily wage: Average gross real daily wage of all regularly, full-time employed workers in real euros.

Table 2: Descriptives of Curriculum Updates

	A. Unweighted		*B. Empl. Weighted*	
	Mean	SD	Mean	SD
Any update	0.038	0.192	0.051	0.220
Type of update:				
Content update only	0.021	0.143	0.025	0.155
Content update + renaming	0.015	0.123	0.023	0.150
Content update + aggregation	0.010	0.098	0.020	0.140
Content update + segregation	0.003	0.053	0.004	0.065
Years until update | update = 1†	15.3	7.8	14.3	7.4

SD - Standard deviation. All variables are binary. *Any update:* Indicates that the curriculum was changed. *Content update only:* Indicates that the content of the curriculum was changed without renaming, aggregation, or segregation. *Renaming:* Indicates that the title of the occupation was changed independent of the type of change. *Aggregation:* Indicates that the occupation was merged with another occupation. *Segregation:* Indicates that the occupation was split into several occupations. A training occupation may be split into several successors, each of which is an aggregation of multiple predecessors; and aggregations and segregations may also be accompanied by renaming. These types of updates are therefore not mutually exclusive and the sum across update types is larger than the total number of updates. Numbers based on the yearly panel, 11,843 observations in panel A and 11,709 observations in panel B. † – Based on initial observations only, 455 observations in panel A and 444 observations in panel B.

Table 3: Examples of Most and Least Updated Occupations

Training Occupation	Broad Occupation	Pr(Update) Per Year
A. Examples of Most Updated Training Occupations		
Flexograph	Production	0.12
Electronics technician for automation technology	Production	0.10
Industrial mechanic	Production	0.10
Electrician	Production	0.09
Retail clerk	Business service	0.09
Automobile mechanic	Production	0.09
Electronics technician for aeronautical systems	Production	0.09
Decor template maker	Production	0.09
Chemical technician	IT + scientific service	0.08
Packaging technologist	Production	0.08
B. Examples of Least Updated Training Occupations		
Gardener	Production	0.02
Manufactured porcelain painter	Production	0.02
Foundation engineering specialist	Production	0.01
Civil engineer	Production	0.01
Road builder	Production	0.01
Asphalt builder	Production	0.01
Wooden toy maker	Production	0.01
Toy manufacturer	Production	0.01
Industrial insulator	Production	0.01
C. Examples of Training Occupations Without Updates		
Brass instrument maker	Production	0.00
Delivery driver	Other commercial service	0.00
Floor layer	Production	0.00
Gilder	Production	0.00
Glass blower	Production	0.00
Hotel clerk	Personal service	0.00
Makeup artist	Personal service	0.00
Stage painter and sculptor	Personal service	0.00
Woodcarver	Production	0.00

Training occupations associated with the most/least updated KldB occupations.

Table 4: Most and Least Technology-Exposed Training Occupations

Training Occupation	Broad Occupation
A. 10 Most Exposed Training Occupations	
Electronics technician for machines and drive technology	Production
Electronics technician for industrial engineering	Production
Electronics technician for devices and systems	Production
Industrial mechanic	Production
Electronics technician for information and system technology	Production
Electronics technician for building and infrastructure systems	Production
Cutting machine operator	Production
Plant mechanic	Production
Electronics technician for automation technology	Production
Tool mechanic	Production
B. 10 Least Exposed Training Occupations	
Plant technologist	Production
Leather production and tanning technology specialist	Production
Factory fireman	Business service
Ice cream specialist	Personal service
Confectionery technologist	Production
Wine technologist	Production
Candle and wax maker	Production
Concrete and terrazzo manufacturer	Production
Flat glass technologist	Production
Bespoke shoemaker	Personal service

Ranked by number of linked digital patents demeaned within years.

Table 5: Curriculum Updates and Digital Technology Exposure

	(1)	(2)	(3)	(4)
	A. Unweighted			
Digital Tech Exposure	0.44***	0.47***	0.51***	0.49***
	(0.09)	(0.10)	(0.10)	(0.10)
N	10,729			
	B. Weighted by initial employment share			
Digital Tech Exposure	0.84***	0.79***	0.79***	0.82***
	(0.17)	(0.17)	(0.16)	(0.15)
N	10,729			
Initial Curriculum Year	X	X	X	X
Year	X	X	X	X
Broad Occ		X	X	X
Broad Occ × Year			X	X
Initial Empl. Share				X

Dependent variable: Dummy for curriculum update. Linear probability models, coefficients multiplied by 100. Initial curriculum year fixed effects in five year bins. Standard errors clustered by 4 digit occupation. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table 6: 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.

Table 7: Descriptives of Vocationally Trained Occupational Incumbents

	Mean	SD	Median
Age	41.09	10.01	40
Year of birth	1959	12	1960
Female	0.43	0.49	0.00
Average daily wage (euros)	91.24	50.00	87.84
Annual daily wage growth	0.01	0.31	0.01
Annual days employed	297	129	365
Annual labor earnings (euros)	27,661	20,559	28,082
Firm size	711	3,040	68
Job mobility (year-to-year):			
Occupation	0.12	0.32	0.00
Industry	0.11	0.31	0.00
Firm	0.16	0.36	0.00

SIEED, full sample prior to stacking. $N = 50,554,417$ worker by year observations.

Online Appendix

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A Data and measurement

A.1 SIEED data construction details

We use SIEED data for two distinct analyses that require different sample constructions: labor market entrants (Section 4.2) and occupational incumbents (Section 4.3). We begin by describing the common data preparation steps, then detail the construction of each sample.

Common data preparation. We prepare the SIEED data following Dauth and Eppelsheimer (2020). We derive career indicators—including tenure and cumulative days in employment—from the administrative spell records, merge individual-level spells with employer characteristics (location, industry, and size) from the Establishment History Panel (BHP), and deflate wages to 2015 euros using the consumer price index. Wages in SIEED are top-coded at the upper social security contribution limit; we impute censored wages following Dauth and Eppelsheimer (2020), who estimate Tobit wage equations by year-region-education cells, augment them with leave-one-out worker and plant wage means to approximate fixed effects, and replace censored log wages with draws from the implied truncated log-normal distribution before transforming them back into Euros. When workers hold multiple concurrent employment spells, we retain the spell with the longest tenure as the main spell. We measure daily wages as the average across all spells within each calendar year, weighting by spell duration. We only retain workers who hold a vocational training degree, and drop workers trained in East Germany, since East German employment records are only available from 1992 onward.

Identifying vocational training episodes. To assign vocational training vintages to workers, we need to know their start and end dates of vocational training. We identify each worker's vocational training episode from the spell structure. We define the start of vocational training as the beginning of the first employment spell flagged as an apprenticeship, provided no prior completed apprenticeship appears in the worker's education history. The training occupation is the occupation code of that spell. We define completion as the end of an apprenticeship spell that is followed by a non-training spell, with the worker's education record simultaneously reflecting a completed vocational qualification.[41] We drop workers who switched training occupations during their apprenticeship or have implausibly short or long training durations (below 1.75 or above 4.25 years).

Sample of labor market entrants. We define labor market entrants as vocationally trained workers observed in the first five years after completing their apprenticeship. We

[41] We impose no restriction on the interval between training completion and subsequent employment. We drop workers who never find socially secured employment after their training.

restrict the entrant sample to workers whose training curriculum we observe, dropping workers who began training before the start of the data (1975). Among entrants, wage censoring is rare—0.21 % of spells exceed the contribution ceiling—since early-career wages seldom approach the social security limit.

Sample of occupational incumbents. We define occupational incumbents as vocationally trained workers employed full-time in the same occupation for at least five consecutive years immediately preceding a curriculum update in that occupation, excluding the 12.3% of spells classified as part-time. For incumbents we do not need to observe the training curriculum itself, such that workers who began training before 1975 are also included. Among incumbents, 4.82 % of spells exceed the contribution ceiling.

A.2 ESCO skills

Figure 9 categorizes new and removed words to the European Skills, Competences, Qualifications and Occupations (ESCO) skill categories. We use the transversal skills and competences, skills, and knowledge sections from the ESCO v1.2.1 taxonomy.[42] The list below describes which level 1 skills are included in each of the categories in Figure 2, and gives some examples of these skills where relevant for context:

- **social & communication**: combines 'communication, collaboration and creativity' and 'social and communication skills and competences' — examples are collaborating in teams and networks; communicating; leading others; designing systems and products; advising and consulting; writing and composing; negotiating; presenting information; working with others; promoting, selling, and purchasing.
- **thinking skills**: abbreviates 'thinking skills and competences' — examples are dealing with problems; thinking creatively and innovatively; processing information, ideas and concepts.
- **digital skills**: combines 'information and communication technologies (ICTs)' and 'working with computers' — examples are accessing and analyzing digital data; setting up and protecting computer systems; using digital tools to control machinery; using digital tools for collaboration, content creation and problem solving; programming computer systems.
- **management skills**: examples are building and developing teams; organizing, planning and scheduling work and activities; developing objectives and strategies; allocating and controlling resources; making decisions; leading and motivating; performing administrative activities.

[42] https://esco.ec.europa.eu/en/about-esco/escopedia/escopedia/esco-v12

- **life skills**: abbreviates 'life skills and competences' — examples are applying health-related skills and competences; applying entrepreneurial and financial skills and competences; applying environmental skills and competences.
- **assisting and caring**: examples are counseling; providing health care or medical treatments; preparing and serving food and drinks; providing information and support to the public and clients.
- **generic skills**: abbreviates 'generic programs and qualifications' — examples are literacy and numeracy.
- **self-management**: abbreviation of 'self-management skills and competences' — examples are working efficiently; maintaining a positive attitude; taking a proactive approach; demonstrating willingness to learn.
- **information skills**: examples are monitoring, inspecting and testing; documenting and recording information; analyzing and evaluating information and data; measuring physical properties; conducting studies, investigations and examinations; managing information; calculating and estimating.
- **services**: examples are personal services; hygiene and occupational health services; security services; transport services.
- **health and welfare**: examples are [add level 4 skills]
- **education/social sciences**: combines 'education' with 'social sciences, journalism and information'
- **natural sciences/math**: abbreviates 'natural sciences, mathematics and statistics'
- **business/admin/law**: abbreviates 'business, administration and law'
- **arts and humanities**
- **agriculture**: abbreviates 'agriculture, forestry, fisheries and veterinary'
- **manufacturing/engineering**: combines 'working with machinery and specialized equipment' and 'engineering, manufacturing and construction' — examples are installing, maintaining and repairing mechanical equipment; operating machinery for the manufacture of products; using precision instrumentation and equipment; driving vehicles; installing, maintaining and repairing electrical, electronic and precision equipment.
- **core skills**: abbreviates 'core skills and competences' — examples are mastering languages; working with numbers and measures.

- **physical/manual skills**: combines 'handling and moving', 'constructing', and 'physical and manual skills and competences' — examples are handling and disposing of waste and hazardous materials; moving and lifting; making moulds, casts, models and patterns; sorting and packaging goods and materials; building and repairing structures.

We use all descriptions associated with each skill, including those at more granular levels of the hierarchy (levels 2, 3, and 4) and turn them into a skill vector using TF-IDF weights and GloVe word embeddings. To assign a new or removed curriculum word to a skill cluster, we apply one-step k-means clustering using the embedding centroid of each cluster.

A.3 Additional data descriptives for main analyses

Figure A1a: Excerpts from 1992 Training Curriculum for Process Control Electronics Technician

Regulation
of the vocational training as process control electronics technician
April 2, 1992

[...]

§1

State recognition of the training occupation

The training occupation process control electronics technician recognized by the state.

§2

Training duration

The vocational training takes three and a half years.

§3

Apprenticeship profile

The subject of the vocational training is at least the following knowledge and skills:

[...]

5. Manufacturing of mechanical parts,
6. Making mechanical connections,

[...]

§8

Final exam

[...]

a) Changing or expanding the control of an automatic device, including planning and controlling the work, changing the program and documenting the changes;

[...]

No.	Part of the apprenticeship profile	Knowledge and skills to be imparted
5	Production of mechanical parts (§4 No. 5)	a) Reading single-component drawings taking into account line types, sclaes, dimension entries and symbols for surface quality and making sketches [...]
6	Manufacturing of mecanical connections (§4 No. 6)	a) Making connections using screws, nuts and washers and secure them with safety elements, in particular spring washers, toothed lock washers and paint [...]

Figure A1b: Excerpts from 2003 Updated Training Curriculum for Industrial Electrical Professions (Update of Process Control Electronics Technician)

Regulation
of the vocational training in the industrial electrical professions
July 3, 2003

[...]

§1
State recognition of training occupations

The training occupations (...)
3. Electronics technician for automation technology (...)
are recognized by the state (...).

§2
Training duration

The vocational training takes three and a half years.

§3
Apprenticeship profile

The subject of the vocational training is at least the following knowledge and skills:

[...]
10. Installing and configuring IT systems,
[...]
11. Advising and supporting customers,
[...]

§8
Final exam

[...]

(6) The examinee must design a modification in an automation technology system according to specified requirements. The examinee must show that he/she carries out technical problem analyses, develops solution concepts taking into account regulations, guidelines, cost-effectiveness and operational processes, determines application-oriented system specifications, selects, configures and programs hardware and software components, adapts circuit documents and can use standard software.

No.	Part of the apprenticeship profile	Knowledge and skills to be imparted
5	Operational and technical communication (Para. 1 No. 5 of §§6, 10, 14, 18, 22 and 26)	[...] e) Conducting conversations with superiors, employees and in a team in a way that is appropriate for the situation and solution-oriented [...] k) Solving problems in a team [...]
10	Installing and configuring IT systems (Para. 1 No. 5 of §§6, 10, 14, 18, 22 and 26)	a) Selecting hardware and software components b) Installing and configuring operating systems and applications c) Integrating IT systems into networks [...]
12	Technical order analysis, solution development (Para. 1 No. 12 of §14)	[...] b) Considering process relations across interfaces and taking into account their interactions in automation systems [...]
13	Implementation of automation technology equipment (Para. 1 No. 13 of §14)	[...] d) Mounting sensors and actuators [...] g) Installing, testing and commissioning of signal and data transmission systems [...]

Figure A1c: Excerpts from 1978 Training Curriculum for Industrial Clerk

Regulation
of the vocational training as industrial clerk
January 24, 1978

[...]

§1

State recognition of the training occupation

The training occupation industrial clerk is recognized by the state

§2

Training duration

The vocational training takes three years.

§3

Apprenticeship profile

The subject of the vocational training is at least the following knowledge and skills:

[...]

b) Purchasing

[...]

c) Sales,

[...]

c) Payment transactions

[...]

§8

Final exam

[...]

The examinee must show by means of practical business processes and facts that he understands business and economic relationships and that he is able to solve practical tasks.

[...]

No.	Part of the apprenticeship profile	Knowledge and skills to be imparted
1.2	Purchasing (§3 No. 1 Letter b)	[...] a) Compiling, evaluating and supplementing purchasing documents [...] g) Processing offers h) Processing order [...]
5.2	Bookkeeping (§3 No. 5 Letter b)	[...] b) Assigning documents to accounts c) Registering accounting documents [...]

Figure A1d: Excerpts from 2002 Updated Training Curriculum for Industrial Clerk

Regulation
of the vocational training as industrial cleark
July 23, 2002

[...]

§1

State recognition of the training occupation

The training occupation industrial clerk is recognized by the state.

§2

Training duration

The vocational training takes three years.

§3

Apprenticeship profile

The subject of the vocational training is at least the following knowledge and skills:

[...]

3.2 Information and communication systems,

[...]

3.4 Teamwork, communicationa dn presentation,

[...]

a) Electronic procurement (e-procurment)

[...]

b) Electronc commerce (e-commerce)

[...]

§8

Final exam

[...]

[...] the examinee must handle processes and complex issues in case studies (...) and show that he can analyze business processes and develop problem-solving solutions in a result-and costumer-oriented manner.

[...]

No.	Part of the apprenticeship profile	Knowledge and skills to be imparted
3.2	Information and communication systems (§4 Para. 1 No. 3.2)	[...] d) Using the operating system, standard software and company-specific software e) Entering data and information [...]
3.3	Planning and Organization (§4 Para. 1 No. 3.3)	a) Setting goals, ordering and scheduling tasks b) Analyzing problems, developing and evaluation alternative solutions [...]
3.4	Teamwork, communication and presentation (§4 Para.1 No. 3.4)	[...] b) Planning and working on tasks in a team, coordinating and evaluating results [...]

Figure A2: Distribution of Wages for Occupations With and Without Vocational Training Curriculum

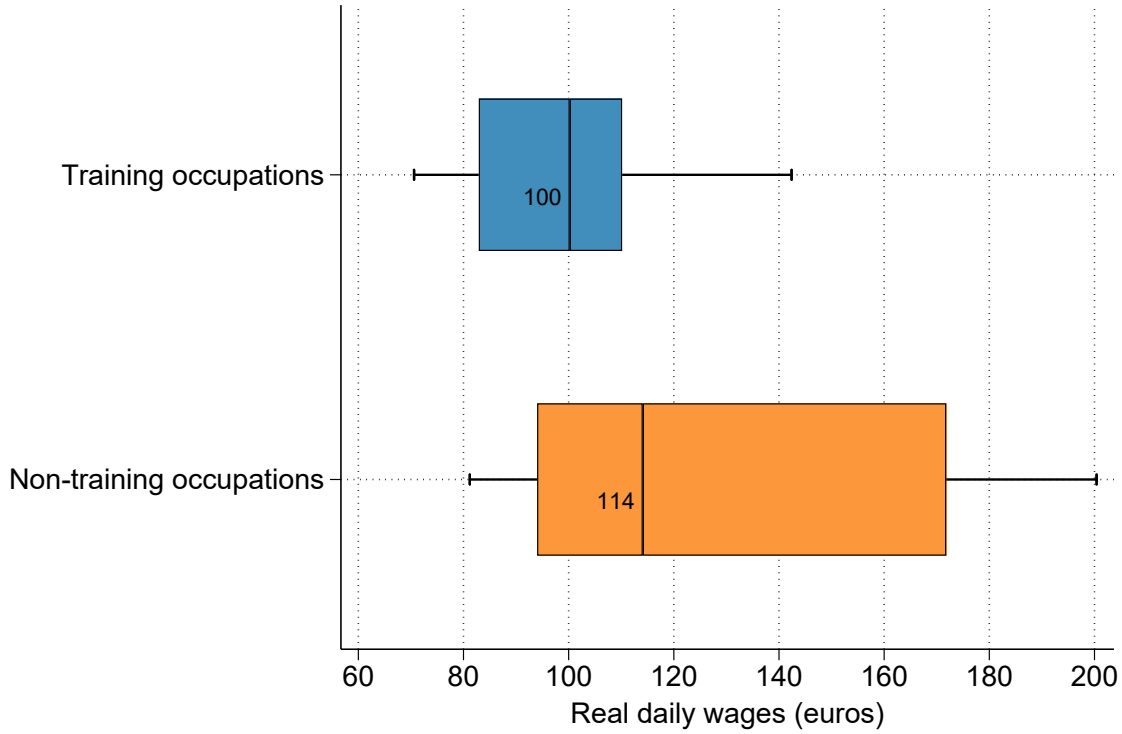


Figure shows a boxplot of real daily wages for occupations with and without a vocational training curriculum (base year for deflation: 2015) based on SIAB data. Vertical lines indicate the median; boxes reflect the interquartile range; and whiskers indicate the 10th and 90th percentiles. Occupations weighted by employment.

Figure A3: Distribution of Wages for Vocationally Trained Workers vs. Others

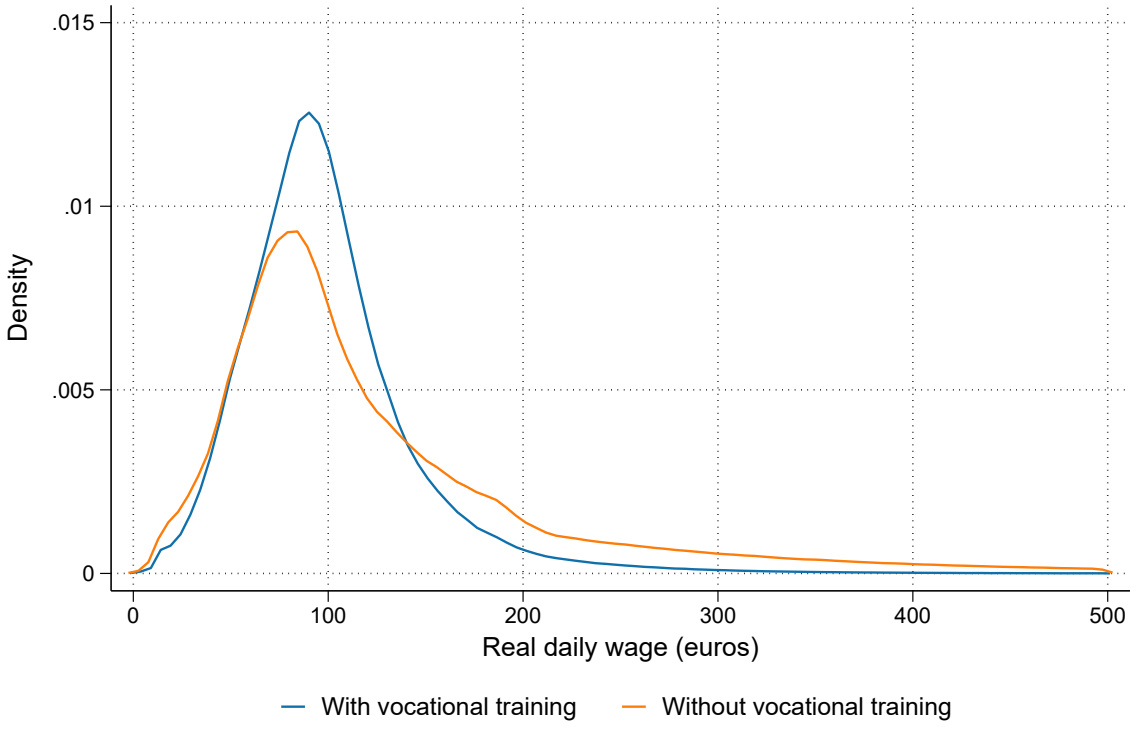
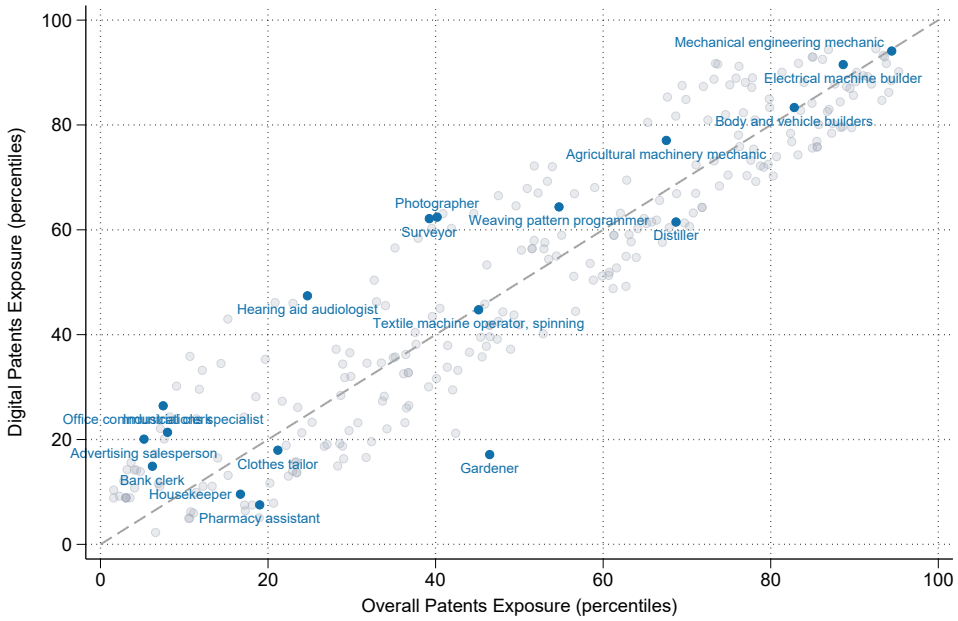


Figure plots the distribution of real daily wages (up to 500 euros) for vocationally trained workers versus all others based on SIAB data.

Figure A4: Digital and Overall Technology Exposure of Training Curricula

A. Average over 1971–1997



B. Average over 1998–2021

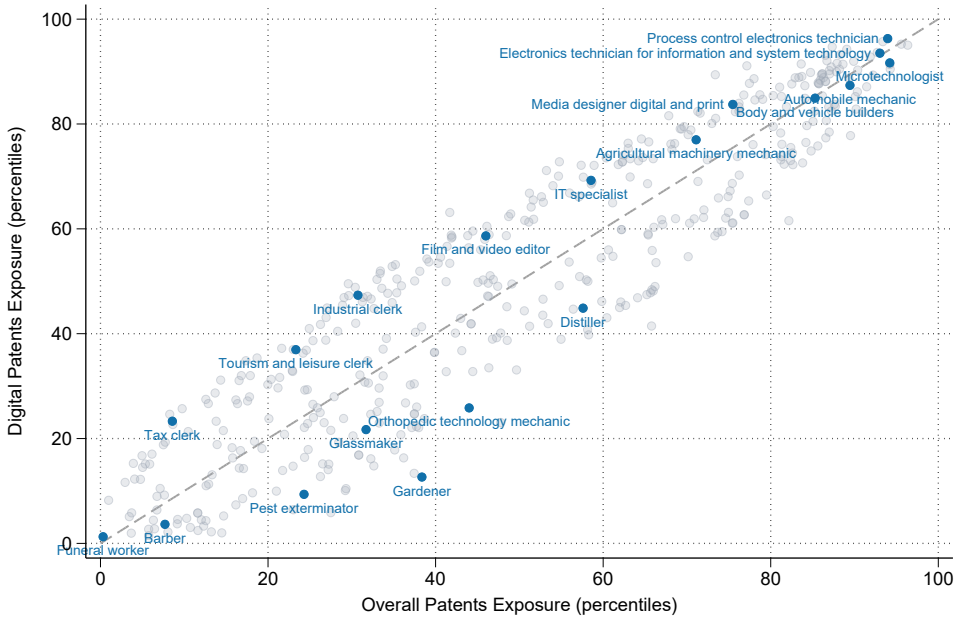
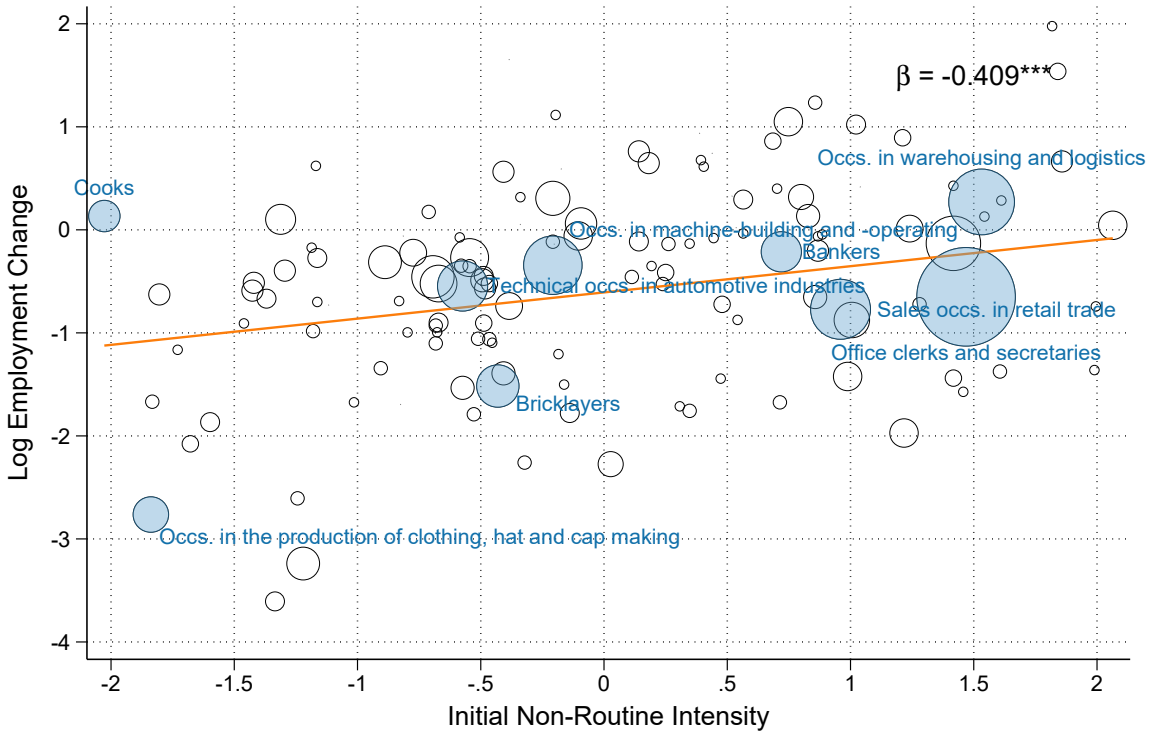


Figure presents a scatter plot of the relationship between occupational exposure to overall and digital patents for 1971–1996 (panel A) and 1997–2021 (panel B). Each point corresponds to the average percentile of overall ($x-$axis) and digital ($y-$axis) exposure of one occupational curriculum, where the average is taken over 1971–1996 ($N = 285$ occupations) in panel A and over 1997–2021 ($N = 451$ occupations) in panel B. The 45 degree line in each panel is plotted with dashes.

Figure A5: Employment Change by Initial Non-Routine Task Intensity



Source: SIAB. Y-axis: Change in occupational regular full-time log employment between 1975 and 2017. The x-axis reflects standardized non-routine intensity of the first curriculum observed in this occupation. For occupations with a training curriculum only. Weighted by the initial employment share in 1975.

Table A1: Stated Reasons for Curriculum Updates, 2011–2021

Category and examples of subcategories	Count
Miscellaneous modernization needs, e.g.:	**130**
Curriculum age	55
Occupational title	12
Qualification requirements	12
Fit/precision of occupational definition	11
Technological change, e.g.:	**115**
Digitalization	32
Changes in materials and methods	25
Changes in products, equipment and systems	16
Changes in processes	14
Changes in competences and qualifications, e.g.:	**97**
Growth of competences	59
Decline or disappearance of competences	8
Delimitation of occupations, e.g.:	**96**
Change in official structuring of additional competences etc.	44
Occupational group formation	13
Joint training provision of several occupations	11
Content overlap of occupations	11
Differentiation from other occupations	9
Merging of occupations	8
Formal framework conditions, e.g.:	**80**
Structuring of regulations and framework curricula	29
Adjustment to recommendation of the BIBB main committee	28
(De-)merging of training occupations / differentiations	19
Deviating training duration	4
Examination, e.g.:	**62**
Examination format	37
Examination structure	10
Examination content	4
Examination economy/efficiency	4
Firm-level structural change, e.g.:	**40**
Task-related and work-organizational change	21
Specialization of company offerings	4
Educational policy challenges, e.g.:	**40**
Permeability of the education system	20
Environment and sustainability	8
Quality of vocational education and training	5
Demographic change	3
Conceptual design criteria for training occupations, e.g.:	**34**
Competence orientation	26
Action and practice orientation	4
Process orientation	4
Attractiveness of occupations	**18**
Number of training places	6
Legal regulations	**18**
Societal change	**15**
Market developments	10
Customer requirements	5

Reasons for update for the 135 update proposals submitted over 2011–2021; multiple reasons possible. Most categories also contain a 'miscellaneous' subcategory which is not separately shown here, but counts towards the category's total frequency. Source: Schad-Dankwart et al. (2023).

Table A2: Number of Tokens per Curriculum Section

	Mean	p10	Median	p90
Exam	3,562	1,158	2,287	5,617
Skills and Knowledge	16,215	2,844	5,415	18,416
Training Framework Curriculum	22,023	7,927	16,396	39,257
Total	43,001	14,967	25,872	75,419

Total includes text not belonging to any of the mentioned categories.

Table A3: Examples of Digital Patent – Curriculum Pairs

Training Occupation	Linked patent example
Body and vehicle builders	Self-gauging sensor assembly
Communications electronics technician	Method and apparatus for high frequency wireless communication
Courier, express and postal services clerk	Internet billing method
Dental technician	Process for making a prosthetic implant
Digitization management clerk	Process and system for predictive resource planning
E-commerce clerk	Method and architecture for multi-level commissioned advertising on a computer network
Engraver	Document inscribing machine
Film and video editor	Karaoke apparatus and method for medley playback
Office communications clerk	Multi-facility appointment scheduling system
Postal service specialist	Computer-aided prepaid transmittal charge billing system
Precision optician	Modular electronic instrument system having automated calibration capability
Radio electronics technician	Electronic circuit
Shipbuilder	Wind velocity sensor for sailboat
Social security clerk	Self-implementing pension benefits system
Tax clerk	Electronic income tax refund early payment system
Travel agent	Computer travel planning system

The table shows the title of the most similar digital breakthrough patent for each example training occupation.

Table A4: Descriptive Statistics of Technology Exposure

	A. Yearly Panel				*B. Initial Observations*			
	Unweighted		Weighted		Unweighted		Weighted	
	Mean	SD	Mean	SD	Mean	SD	Mean	SD
Digital Tech Exposure – Full Text	3.86	2.58	4.17	2.59	3.87	2.61	4.26	2.66
Digital Tech Exposure – Exam	4.11	2.57	3.89	2.78	3.81	2.63	3.67	2.74
Overall Tech Exposure – Full Text	5.53	2.24	5.57	2.23	5.36	2.46	5.51	2.44

SD - Standard deviation.

Table A5: Most and Least Technology-Exposed Training Occupations

Most Exposed Training Occupations	Least Exposed Training Occupations
A. Business service	
Wholesale and foreign trade management clerk	Factory fireman
Media designer digital and print	Pharmaceutical clerk
Media designer image and sound	Tax clerk
B. IT + scientific service	
IT system management clerk	IT clerk
Digitization management clerk	Information and telecommunications system clerk
IT specialist	Dairy laboratory technician
C. Other commercial service	
Construction equipment operator	Letter and freight traffic specialist
Plumber	Swimming pool safety specialist
Event technology specialist	Legal clerk
D. Personal service	
Housekeeper	Bespoke shoemaker
Optometrist	Ice cream specialist
Food technology specialist	Audiologist
E. Production	
Electronics technician for devices and systems	Flat glass technologist
Electronics technician for industrial engineering	Concrete and terrazzo manufacturer
Electronics technician for machines and drive technology	Candle and wax maker

Ranked by number of linked digital patents demeaned within years.

Table A6: O*NET Items Included in Routine and Non-Routine Task Scores

Task	O*NET Item
Non-routine analytic	Analyzing data/information
Non-routine analytic	Thinking creatively
Non-routine analytic	Interpreting information for others
Non-routine interpersonal	Establishing and maintaining personal relationships
Non-routine interpersonal	Guiding, directing and motivating subordinates
Non-routine interpersonal	Coaching/developing others
Routine cognitive	Performing administrative activities
Routine manual	Controlling machines and processes
Non-routine manual	Operating vehicles, mechanized devices, or equipment

O*NET items are as in Acemoglu and Autor (2011) where possible: this means the item has to have a detailed textual description.

Table A7: Most and Least Non-Routine-Intense Training Occupations

Training Occupation	Broad Occupation
A. Most Non-Routine-Intense Training Occupations	
Event manager	Other commercial service
Tourism and leisure clerk	Personal service
Railway and road traffic clerk	Other commercial service
Driving operations specialist	Other commercial service
Legal administrative assistant	Business service
Traffic service clerk	Other commercial service
Market and social research specialist	Business service
Marketing communication clerk	Business service
Personnel services clerk	Business service
Sports specialist	Personal service
B. 10 Least Non-Routine-Intense Training Occupations	
Thermometer maker	Production
Glass apparatus builder	Production
Basket maker	Production
Baker	Personal service
Dressmaker	Production
Clothes tailor	Personal service
Men's tailor	Personal service
Glassmaker	Production
Confectioner	Personal service
Embroiderer	Production

Non-routine intensity demeaned within years.

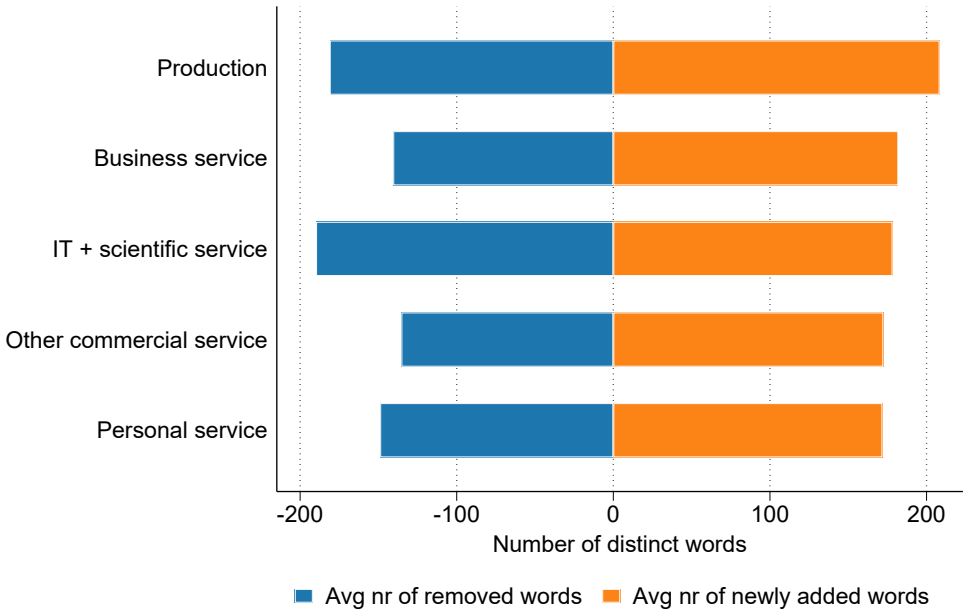
Table A8: Most and Least Non-Routine-Intense Training Occupations

Most Non-Routine-Intense	Least Non-Routine-Intense
A. Business service	
Legal administrative assistant	Pharmaceutical clerk
Market and social research specialist	Media designer image and sound
Marketing communication clerk	Legal assistant
B. IT + scientific service	
IT clerk	Chemical laboratory technician
IT system management clerk	Dairy laboratory technician
Information and telecommunications system clerk	Material tester
C. Other commercial service	
Event manager	Plumber
Railway and road traffic clerk	Interior decorator
Driving operations specialist	Brewers and malters
D. Personal service	
Tourism and leisure clerk	Clothes tailor
Sports specialist	Men's tailor
Travel agent	Confectioner
E. Production	
Road and traffic engineering specialist	Dressmaker
IT system electronics technician	Glassmaker
Information and telecommunications systems electronics technician	Embroiderer

Non-routine intensity demeaned within years.

Figure A6: Removed and Newly Added Words in Curriculum Updates

A. Number of Words



B. Number of Words as Share of Prior Curriculum Words

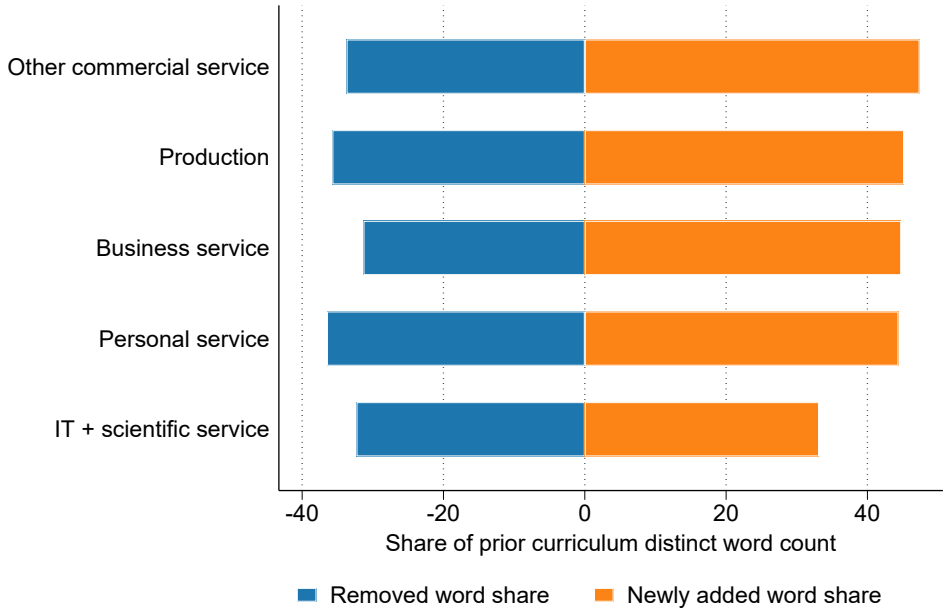


Figure presents the average number of distinct removed and distinct newly added words across curriculum updates in absolute number (panel A) and as a share of distinct prior curriculum word counts (panel B), by broad occupation.

Figure A7: Removed and Added Word Shares Across Training Occupations

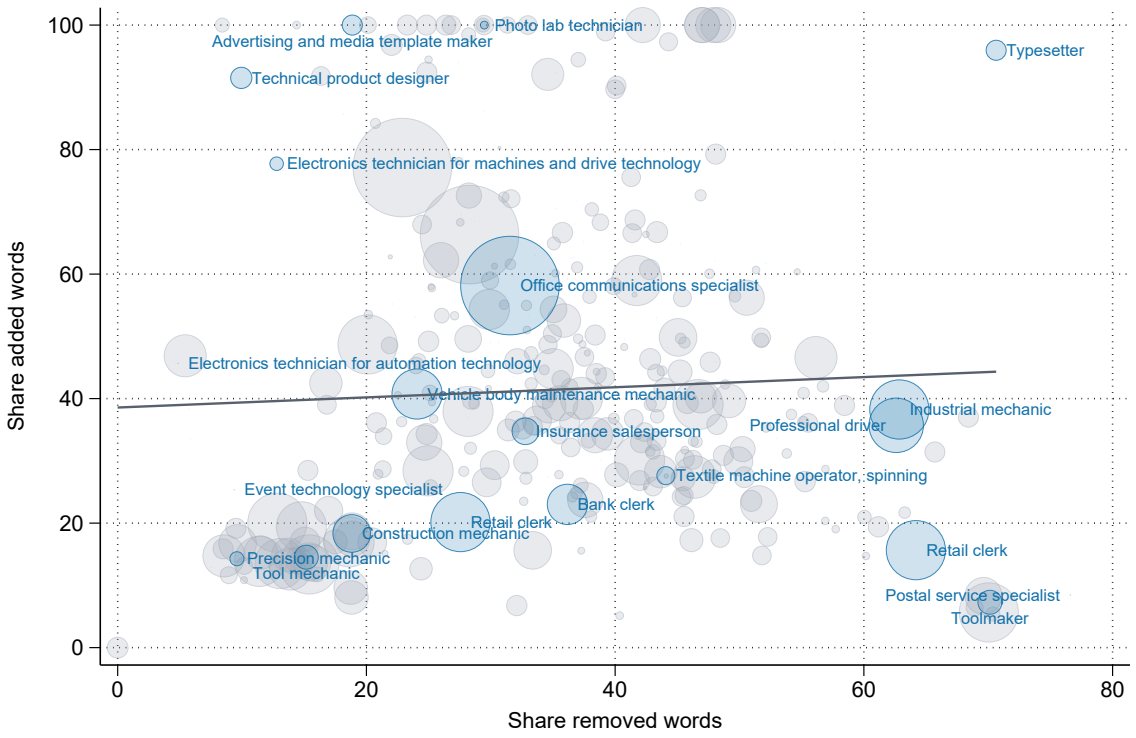


Figure reports the share of removed words against the share of added words for curriculum updates. The size of circles reflects average occupational employment shares.

B Curriculum change

B.1 Curriculum updates

This appendix presents additional results and robustness checks to supplement the baseline analysis of curriculum updates in Section 3.

B.1.1 Curriculum updates: Duration models

Our baseline specification in Table 5 uses a linear probability model on an annual panel of training occupations, treating curriculum updates as a binary outcome. A natural alternative is a discrete-time duration model, which directly models the hazard of updating as a function of time since curriculum inception and accounts for the survival structure of the data. We estimate a so-called complementary log-log model—the discrete-time analog of a continuous-time proportional hazards model (Prentice and Gloeckler, 1978; Jenkins, 1995)—on the same annual panel:

$$\log\Big(-\log\Big(1-\Pr(\text{Update}_{kjt}=1)\Big)\Big) = \beta \text{Tech}_{kj,[t-25;t-20]} + \gamma_t + \zeta_J + \theta_d + \delta \frac{E_{jt_0}}{E_{t_0}}.$$

The left-hand side captures the log of the yearly increase in the cumulative hazard of updating. θ_d captures duration dependence (years since curriculum inception), replacing the curriculum inception year controls used in the linear probability model. Calendar year fixed effects (γ_t), broad occupation fixed effects (ζ_J), and initial occupational employment share ($\frac{E_{jt_0}}{E_{t_0}}$) enter as before. Standard errors are clustered by occupation.

Table B1 reports results. Because raw coefficients of a complementary log-log model do not have a direct marginal effect interpretation, we transform them to show the percentage change in the conditional annual update hazard from a 10% increase in digital technology exposure.[43] In the most saturated specification (column 4), this effect is 4.9% (unweighted) and 5.5% (employment-weighted). These are large effects, confirming that technology exposure is a strong predictor of curriculum updating. While these effects are not directly comparable to the linear probability estimates—which give percentage point changes rather than proportional changes in the hazard—both specifications confirm that technology exposure is a strong and robust predictor of curriculum updating.

[43] Reported coefficients are transformed to $\exp(\hat{\beta} \times \ln 1.1) - 1$.

Table B1: Curriculum Updates and Digital Technology Exposure: Duration Models

	(1)	(2)	(3)	(4)
		A. Unweighted		
Digital Tech Exposure	0.031***	0.030***	0.050***	0.049***
	(0.005)	(0.005)	(0.006)	(0.006)
N		9,921		
		B. Weighted by initial employment share		
Digital Tech Exposure	0.030***	0.025***	0.053***	0.055***
	(0.005)	(0.005)	(0.009)	(0.010)
N		9,921		
Year	X	X	X	X
Broad Occ		X	X	X
Year Since Initial Curriculum			X	X
Initial Empl. Share				X

Discrete-time proportional hazard estimates of the effect of digital technology exposure on curriculum updates. The unit of observation is a training occupation–year. Coefficients are transformed to show the percentage change in the conditional annual update hazard from a 10% increase in digital technology exposure. Panel B weights observations by initial occupational employment share. "Years Since Initial Curriculum" controls for duration dependence in years. Standard errors clustered by training occupation in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

B.1.2 Curriculum updates: Intensive margin effects

We supplement our baseline annual panel analysis with a cross-sectional approach examining the duration until curricula are updated. Using each curriculum's first observation, we estimate:

$$\text{Years until update}_{kj(\tau)} | \{\mathbb{1}(\text{Update})_{kj} = 1\} = \beta \text{Tech}_{kj,[\tau-25;\tau-20]} + \theta_{kj,\tau} + \zeta_J + \delta \frac{E_{jt_0}}{E_{t_0}} + \varepsilon_{kj(\tau)} \tag{B1}$$

where k indexes curricula, j training occupations, and τ the first year a curriculum is observed. The dependent variable measures years until a curriculum update occurs, conditional on an update being observed.[44] The independent variable of interest is each curriculum's initial technology exposure, defined as before. We control for curriculum inception year in five year bins ($\theta_{kj,\tau}$) and, in some specifications, broad occupation fixed effects (ζ_J) and initial occupational employment size ($\frac{E_{jt_0}}{E_{t0}}$). This specification examines the intensive margin only: *given* that a curriculum is updated, does technology exposure accelerate the update? Here, we expect $\beta < 0$, reflecting that technology-exposed occupations are updated more rapidly.

Table B2 shows that technology-exposed occupations update more rapidly. Doubling technology exposure accelerates updates by approximately 5 months ($= -0.63\times \ln(2) \times 12$ months, column 3 of panel A). A one standard deviation increase in technology exposure of 2.58 reduces time to update by 1.6 years, or 11% relative to the mean duration of 15.3 years (reported in Table 2). Results hold in both unweighted (panel A) and employment-weighted models (panel B), and remain robust to controlling for broad occupation fixed effects and occupational employment size. Technology exposure thus affects both the extensive margin (whether curricula update) and intensive margin (how quickly they update), though the extensive margin effect is quantitatively more important.

[44] For curricula merging into more than one training occupation in different years, we use the time until the earliest change.

Table B2: Years until Curriculum Updates and Digital Technology Exposure

	(1)	(2)	(3)
		A. Unweighted	
Digital Tech Exposure	-0.47^{**}	-0.62^{**}	-0.63^{***}
	(0.17)	(0.19)	(0.19)
N		375	
	B. Weighted by initial employment share		
Digital Tech Exposure	-0.50^{*}	-0.59^{*}	-0.68^{**}
	(0.23)	(0.23)	(0.21)
N		375	
Initial Curriculum Year	X	X	X
Broad Occ		X	X
Initial Empl. Share			X

Dependent variable: Years until curriculum update. Initial curriculum year fixed effects in five year bins. Standard errors clustered by 4 digit occupation. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

B.1.3 Curriculum updates: Robustness checks

Timing of technology effects. To explore the time lag between breakthrough technology exposure and curriculum updates, we use local projections (Jordà, 2005). We estimate how technology exposure affects curriculum updates over expanding time horizons T:

$$\mathbb{1}(\text{Update})_{kj[t+T]} = \beta \text{Tech}_{k,[t-5;t]} + \eta \text{Tech}_{kj,[t-5;t-10]} + \gamma_t + \theta_{kj,\tau} + \delta \frac{E_{jt_0}}{E_{t0}} + \zeta_{J\times t} + \varepsilon_{kjt} \quad \text{(B2)}$$

The coefficient β captures how initial technology exposure in years $[t-5;t]$ affects updates T years later. We control for lagged technology exposure ($\text{Tech}_{kj,[t-5;t-10]}$) to address serial correlation in technology exposure, along with year fixed effects (γ_t), initial curriculum year fixed effects ($\theta_{kj,\tau}$), and—in the most saturated specification— initial occupational employment size ($\frac{E_{jt_0}}{E_{t0}}$) and broad occupation by year fixed effects ($\zeta_{J\times t}$). Standard errors are clustered by occupation.

Figure B1 plots the estimated β coefficients for separate regressions with increasing T (blue series). Technology exposure has a minimal immediate effect on curriculum updates: coefficients remain near zero for the first 15 years following technology exposure. From then on, coefficients increase and become statistically significant around the 20-year mark, and remain higher for several years before declining mostly through year 25. This pattern holds qualitatively in the saturated model (orange series), though estimates are noisier. These findings validate our choice of a 20-year lag when measuring breakthrough technology expo-

sure.

Types of curriculum updates. Table B3 examines which types of curriculum change drive our results. We separately analyze curriculum updates that occur (A) without any occupational renaming, aggregation, or segregation; and those accompanied by (B) renaming, (C) aggregation, or (D) segregation.[45] We recode updates distinct from the type considered as 0, to disaggregate the total effect on updates found in panel A of Table 5. Content-only updates— those involving no occupational changes— account for half the total effect of digital technology exposure on curriculum updates (0.25 in panel A, column 4, versus 0.49 in Table 5's panel A). The remaining three update types jointly contribute the other half. Technology exposure significantly predicts each update type individually, including in specifications with the full set of controls. Table B4 shows similar results when weighting models by occupational employment shares.

Other robustness checks. Our findings are robust to changes in how technology exposure is constructed. First, results are similar when only using the exam section of curricula to construct patent links— the high-stakes component describing skills subject to examination. Estimates are smaller and less precise, as expected given that exam sections constitute only 8% of curriculum text (see Table A2). Nonetheless, curricula with exam content more exposed to digital technology update more frequently (Table B5) and more rapidly (Table B6). Second, Table B7 demonstrates that our results hold when measuring technology exposure using *all* breakthrough patents rather than only digital patents, though estimates are somewhat smaller. This confirms that exposure to *digital* technology has particularly strong impacts on curriculum updates over this period, and that exposure to other technologies does not offset this effect. Third, our findings are unaffected by removing the small share of breakthrough patents held by German inventors.

[45] As noted in Section 2, renamings can co-occur with aggregations and/or segregations: around 85% of aggregations or segregations involve occupational renaming. Aggregations and segregations may also co-occur.

Figure B1: Impacts of Digital Technology Exposure on Curriculum Updates Using Local Projections

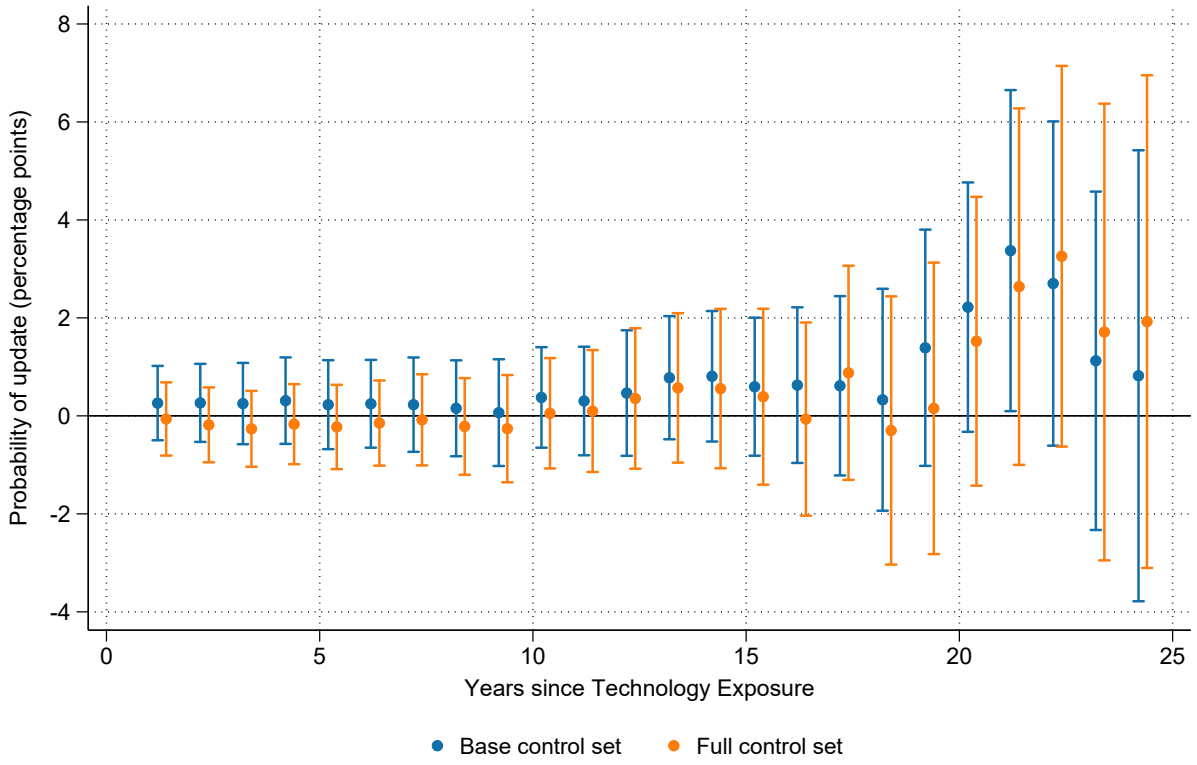


Figure presents estimates of equation (B2). The dependent variable is a dummy for the curriculum being updated (conditional on not having being updated yet). Coefficients multiplied by 100. Standard errors clusted by occupation, whiskers represent 95% confidence intervals.

Table B3: Type of Curriculum Update and Digital Technology Exposure

	A. Content update only				*B. Content update + Renaming*			
Digital Tech Exposure	0.21**	0.22***	0.26***	0.25***	0.21**	0.23**	0.24**	0.23**
	(0.07)	(0.06)	(0.07)	(0.07)	(0.08)	(0.08)	(0.08)	(0.08)
N	10,729				10,729			
	C. Content update + Aggregation				*D. Content update + Segregation*			
Digital Tech Exposure	0.21**	0.21**	0.20*	0.18*	0.07**	0.08*	0.08*	0.08*
	(0.07)	(0.08)	(0.08)	(0.08)	(0.03)	(0.03)	(0.03)	(0.03)
N	10,729				10,729			
Initial Curriculum Year	X	X	X	X	X	X	X	X
Year	X	X	X	X	X	X	X	X
Broad Occ		X	X	X		X	X	X
Broad Occ × Year			X	X			X	X
Initial Empl. Share				X				X

Dependent variable: Dummy for curriculum update type. For each panel, the reference group is the combination of no updates and updates different from the type considered in that panel. Note that the update types in panels B, C, and D are not mutually exclusive, but they are jointly mutually exclusive with the update type in panel A. Linear probability models, unweighted, coefficients multiplied by 100. Initial curriculum year fixed effects in five year bins. Standard errors clustered by 4 digit occupation. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table B4: Type of Curriculum Update and Digital Technology Exposure, Weighted Models

	A. Content update only				*B. Content update + Renaming*			
Digital Tech Exposure	0.35*	0.29	0.43*	0.47**	0.50**	0.50**	0.36*	0.35*
	(0.16)	(0.15)	(0.17)	(0.17)	(0.15)	(0.18)	(0.15)	(0.16)
N	10,729				10,729			
	C. Content update + Aggregation				*D. Content update + Segregation*			
Digital Tech Exposure	0.53***	0.55**	0.38**	0.33*	0.08	0.09	0.09	0.10
	(0.14)	(0.17)	(0.14)	(0.14)	(0.05)	(0.06)	(0.06)	(0.06)
N	10,729				10,729			
Initial Curriculum Year	X	X	X	X	X	X	X	X
Year	X	X	X	X	X	X	X	X
Broad Occ		X	X	X		X	X	X
Broad Occ × Year			X	X			X	X
Initial Empl. Share				X				X

Dependent variable: Dummy for curriculum update type. For each panel, the reference group is the combination of no updates and updates different from the type considered in that panel. Note that the update types in panels B, C, and D are not mutually exclusive, but they are jointly mutually exclusive with the update type in panel A. Linear probability models, weighted by employment size, coefficients multiplied by 100. Initial curriculum year fixed effects in five year bins. Standard errors clustered by 4 digit occupation. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table B5: Curriculum Updates and Digital Technology Exposure, Exam Section Only

	(1)	(2)	(3)	(4)
		A. Unweighted		
Digital Tech Exposure	0.17*	0.20*	0.21*	0.20*
	(0.08)	(0.09)	(0.09)	(0.09)
N		10,455		
		B. Weighted by initial employment share		
Digital Tech Exposure	0.35	0.19	0.15	0.15
	(0.19)	(0.21)	(0.21)	(0.21)
N		10,455		
Initial Curriculum Year	X	X	X	X
Year	X	X	X	X
Broad Occ		X	X	X
Broad Occ × Year			X	X
Initial Empl. Share				X

Dependent variable: Dummy for curriculum update. Linear probability models, coefficients multiplied by 100. Initial curriculum year fixed effects in five year bins. Standard errors clustered at the 5 digit occupation level. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table B6: Years Until Curriculum Update and Digital Technology Exposure, Exam Section Only

	(1)	(2)	(3)
		A. Unweighted	
Digital Tech Exposure	−0.39*	−0.44*	−0.44*
	(0.16)	(0.17)	(0.17)
N		354	
	B. Weighted by initial employment share		
Digital Tech Exposure	−0.16	−0.50*	−0.45*
	(0.21)	(0.24)	(0.22)
N		354	
Initial Curriculum Year	X	X	X
Broad Occ		X	X
Initial Empl. Share			X

Dependent variable: Years until curriculum update. Initial curriculum year fixed effects in five year bins. Standard errors clustered at the 5 digit occupation level. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table B7: Curriculum Updates and Overall Technology Exposure

	(1)	(2)	(3)	(4)
	A. Unweighted			
Overall Tech Exposure	0.22*	0.28**	0.36**	0.34**
	(0.11)	(0.11)	(0.12)	(0.12)
N	11,096			
	B. Weighted by initial employment share			
Overall Tech Exposure	0.65**	0.46*	0.48*	0.49**
	(0.24)	(0.23)	(0.20)	(0.19)
N	11,096			
Initial Curriculum Year	X	X	X	X
Year	X	X	X	X
Broad Occ		X	X	X
Broad Occ × Year			X	X
Initial Empl. Share				X

Dependent variable: Dummy for curriculum update. Linear probability models, coefficients multiplied by 100. Initial curriculum year fixed effects in five year bins. Standard errors clustered by 4 digit occupation. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

B.2 Changes in curriculum content

This appendix presents additional analyses related to changes in curriculum content. First, we use keyword analyses rather than the more comprehensive measurement of routine task content, and second, we present various robustness checks on our baseline results.

B.2.1 Keyword analysis

We examine the emergence of keywords related to digital technology and to social skills in vocational training curricula. Increased digital keyword prevalence in curricula would further validate the technology's role in driving curriculum updates and indicate that workers are being trained to work with these technologies. Social skills are particularly complementary to digital technology (Deming, 2017): we therefore expect rising social skill importance in curricula, especially when they are highly exposed to technology.

For digital technology use, we consider words containing "digital", "software", "computer", "ICT", "online" or "automat" (capturing automate, automation, et cetera). For social skills, we use words containing "team", "collaborat" (capturing collaborate, collaboration, et cetera), or "negotiat" (capturing negotiate, negotiation, et cetera). Results are robust to using narrower keyword sets. Descriptives are reported in Tables B8 and B9. We estimate equation (2) with the occurrence of these digital or social keywords as the dependent variable, among updated curricula.

Figure B2 presents the results. The first row shows the average annual change in digital technology use over time (controlling for 4-digit occupation fixed effects as before). The three panels on this row measure this use in curriculum text as (1) a dummy for the occurrence of any digital keyword; (2) the share of digital keywords; and (3) the absolute number of digital keywords. Digital keywords increase significantly over 1976–2021 across all three measures. Moreover, this increase concentrates in curricula highly exposed to digital technology, bolstering confidence in our exposure measure.

For example, digital keyword occurrence increases by 1.3 percentage points annually among updated curricula, indicating that curriculum texts increasingly include one or more digital keywords. The share of digital keywords in all curriculum text increases by 0.5 percentage points cumulatively over the entire period ($0.12/1{,}000 \times 100$ percentage points annually $\times$ $(2021-1976)$). This pattern is more pronounced for highly technology-exposed curricula, which experience a cumulative increase of 1.0 percentage points ($0.23/1000 \times 100 \times (2021-1976)$). For both the share (second panel, first row) and absolute number (third panel, first row) of digital keywords, the increase is entirely driven by highly technology-exposed curricula. As shown in the third panel, these curricula add more than 1 digital keyword annually on average, while less exposed curricula show no significant change.

The bottom row of Figure B2 shows that social skills have also become significantly more important in vocational training curricula over time, across all three measurement approaches. The rising importance of social skills is substantially more pronounced in highly technology-exposed curricula, which add approximately 0.4 social keywords annually on

average, compared to no perceptible change for less exposed curricula.[46]

Table B8: Descriptive Statistics of Curriculum Keyword Groups

	A. Total		*B. Low tech*		*C. High tech*	
	Mean	SD	Mean	SD	Mean	SD
Digital Keywords						
Occurrence of digital keywords (0/1)	0.44	0.50	0.30	0.46	0.57	0.49
Share of digital keywords (×1,000)	1.13	2.73	0.48	1.09	1.78	3.57
Number of digital keywords	4.00	15.59	0.92	2.10	7.02	21.43
Social Skills Keywords						
Occurrence of social keywords (0/1)	0.36	0.48	0.31	0.46	0.42	0.49
Share of social keywords (×1,000)	0.66	1.28	0.65	1.39	0.66	1.16
Number of social keywords	1.96	5.50	1.26	2.62	2.64	7.24

Table B9: Averages of Detailed Curriculum Keywords

	A. Occurrence (0/1)			*B. Share (×1,000)*			*C. Number*		
	Total	Prod	Svc	Total	Prod	Svc	Total	Prod	Svc
Digital Keywords									
digital*	0.13	0.17	0.07	0.16	0.17	0.16	0.66	0.73	0.53
software*	0.19	0.16	0.25	0.38	0.28	0.57	1.38	1.35	1.42
computer*	0.14	0.14	0.12	0.15	0.17	0.09	0.40	0.48	0.23
ICT	0.19	0.20	0.18	0.26	0.22	0.34	0.84	0.83	0.87
online*	0.01	0.01	0.02	0.02	0.00	0.04	0.06	0.01	0.15
automat*	0.13	0.16	0.09	0.17	0.22	0.08	0.66	0.89	0.18
Social Skills Keywords									
team*	0.33	0.27	0.47	0.60	0.39	1.02	1.79	1.61	2.14
collaborat*	0.06	0.06	0.07	0.03	0.02	0.04	0.08	0.06	0.10
negotiat*	0.04	0.03	0.07	0.03	0.01	0.06	0.09	0.06	0.15

[46]Figure B3 highlights that these patterns exist both in production and service occupations, though are more pronounced in the former. Figure B4 shows qualitatively similar results when not conditioning on curriculum change.

Figure B2: Changes in Digital Technology and Social Skill Use in Updated Curricula, 1976–2021

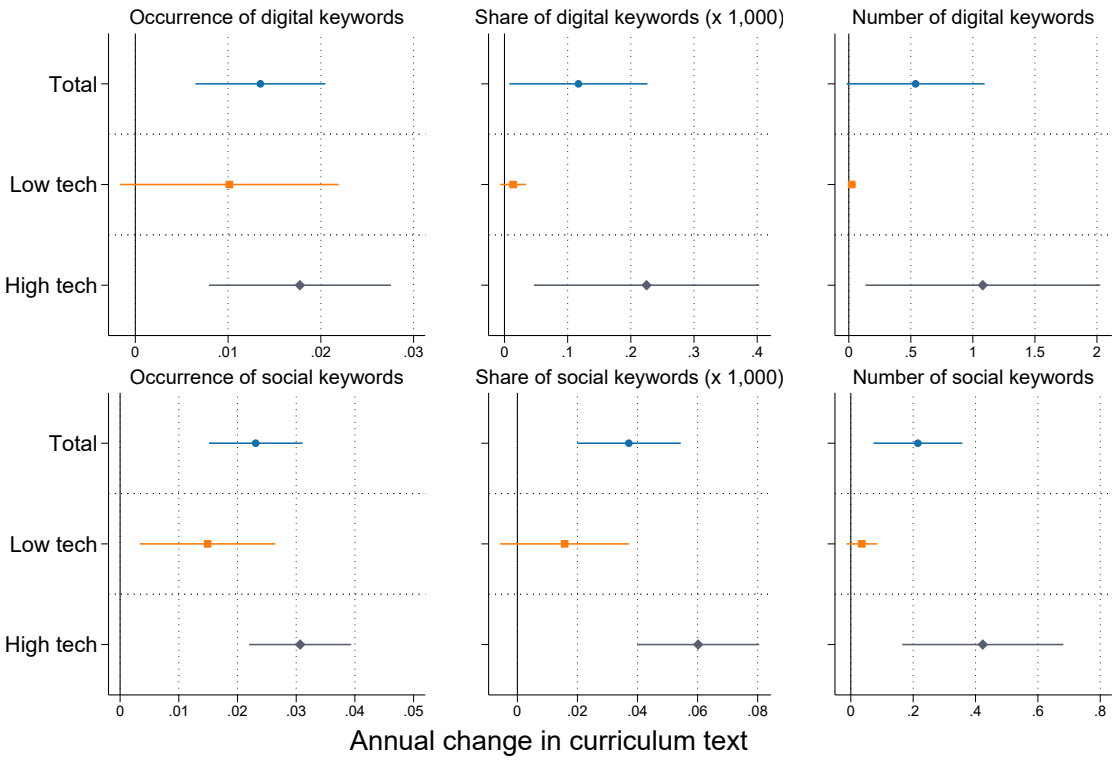


Figure reports coefficients on a linear timetrend, from a regression of keyword occurrence, keyword shares, or keyword counts in vocational training curricula (see equation (2)), for the subsample of curricula with updates over 1976–2021. High tech (low tech) defined as curricula with an initial digital technology exposure above (at or below) the median across all occupations.

Figure B3: Changes in Digital Technology and Social Skill Use in Updated Curricula for Production and Service Occupations, 1976–2021

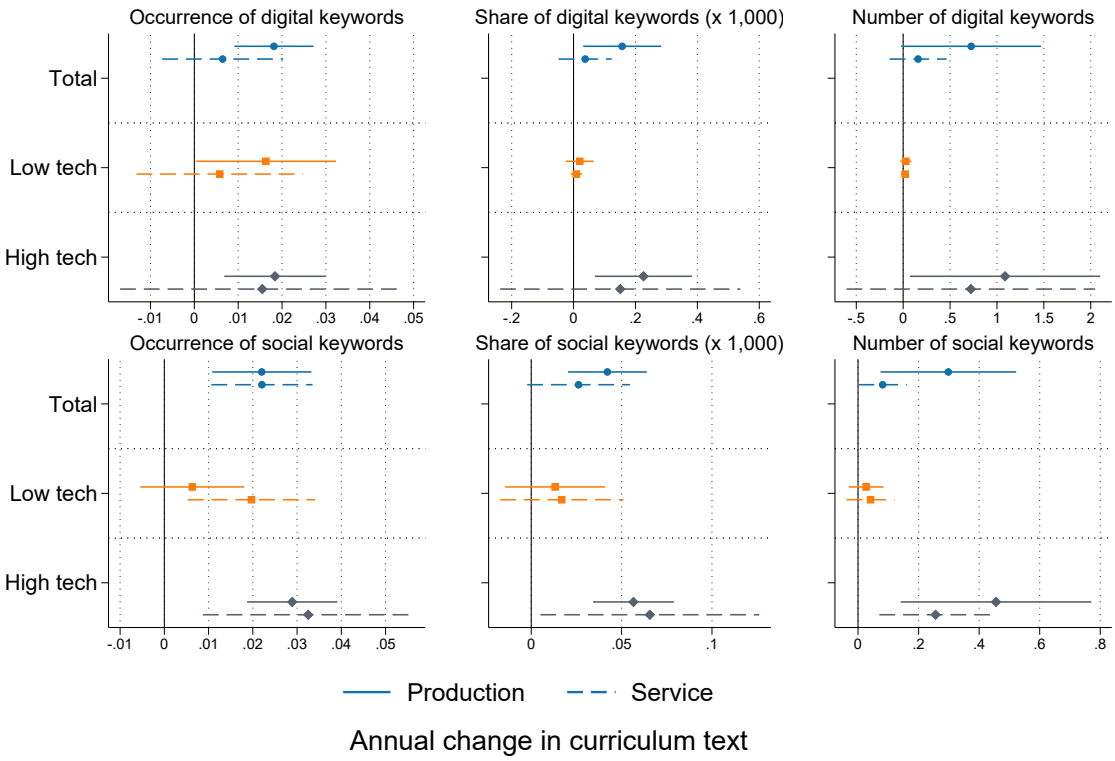


Figure reports coefficients on a linear timetrend, from a regression of keyword occurrence, keyword shares, or keyword counts in vocational training curricula (see equation (2)), for the subsample of curricula with updates over 1976–2021. High tech (low tech) defined as curricula with an initial digital technology exposure above (at or below) the median across all occupations.

Figure B4: Changes in Digital Technology and Social Skill Use in All Curricula, 1976–2021

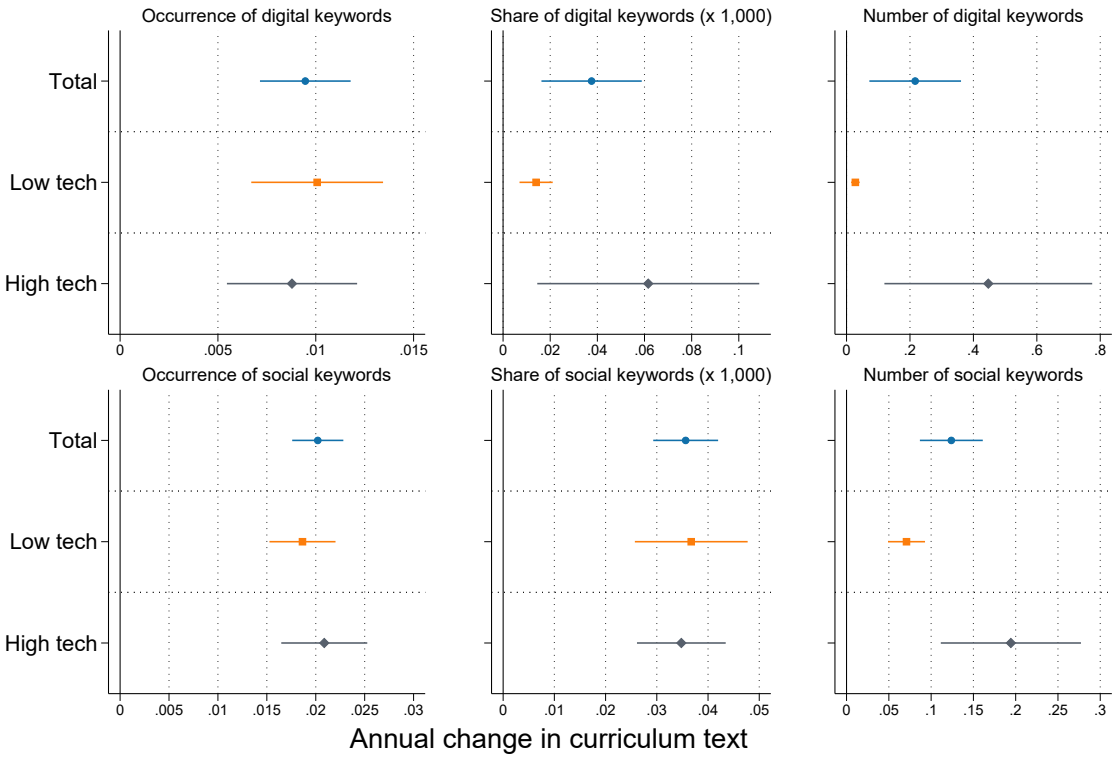


Figure reports coefficients on a linear timetrend, from a regression of keyword occurrence, keyword shares, or keyword counts in vocational training curricula (see equation (2)), for all curricula over 1976–2021. High tech (low tech) defined as curricula with an initial digital technology exposure above (at or below) the median across all occupations.

B.2.2 Changes in complexity

We analyze changes in curriculum complexity, measured by the share of curriculum words outside a typical fourth-grader's vocabulary (Dale and Chall, 1948; Chall and Dale, 1995). Autor and Thompson (2025) argue that word complexity captures expertise: more complex words reflect skills or tasks less easily performed by broad groups of workers, and therefore more expert. At the curriculum level, this complexity score correlates strongly with routine task intensity ($r = -0.63$). Figure B5 shows that curricula are becoming more complex over time, and Figure B6 shows this is mostly driven by new skill emergence.

Figure B5: Changes in Word Complexity in Updated Curricula, 1976–2021

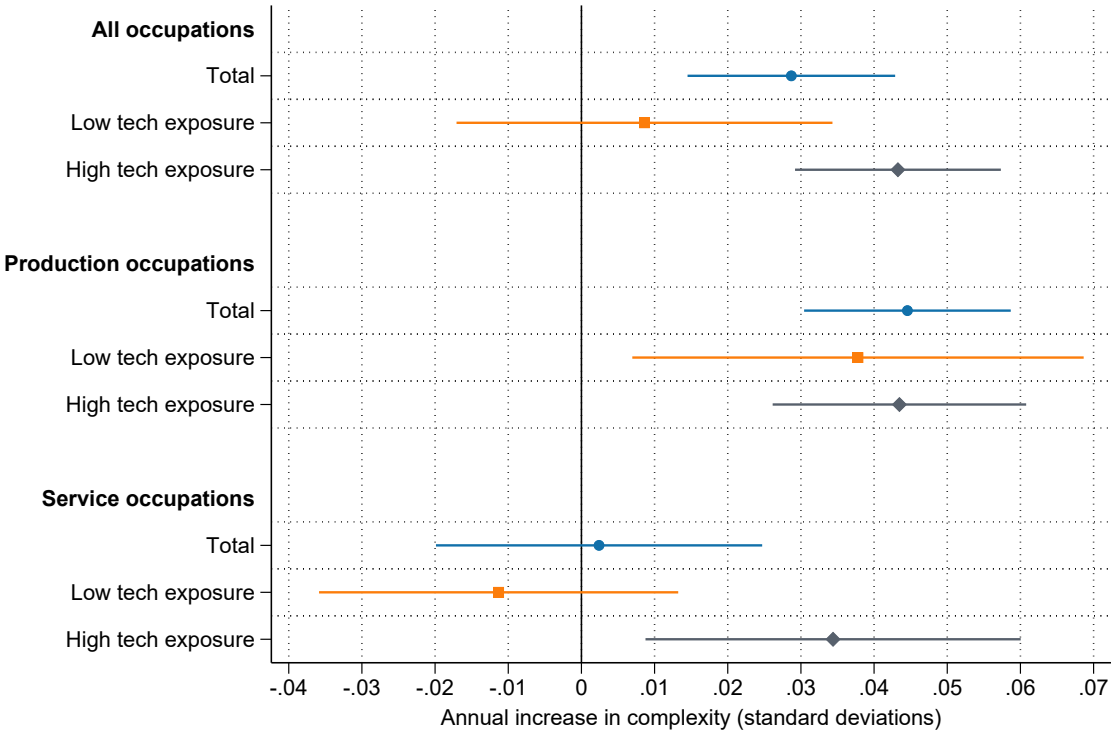


Figure reports coefficients on a linear timetrend, from a regression of complex word shares in vocational training curricula (see equation (2)), for the subsample of curricula with updates over 1976–2021. Complex words are defined as those not in the Dale and Chall (1948) list, following Autor and Thompson (2025). High tech (low tech) defined as curricula with an initial digital technology exposure above (at or below) the median across all occupations.

Figure B6: Changes in Curriculum Complexity from Removed, Remaining, and Newly Added Words

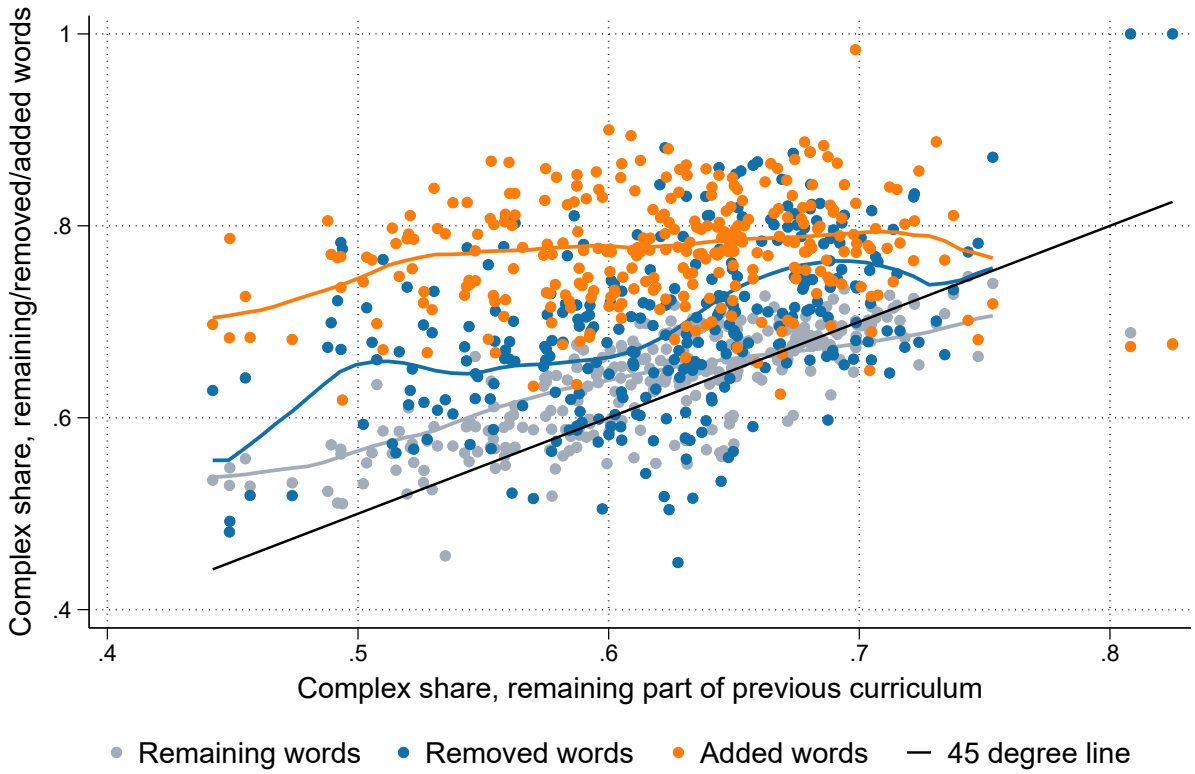


Figure presents the complexity of new curriculum words plotted against remaining words in the previous curriculum. Fitted lines are local polynomials weighted by training occupation employment shares.

B.3 Curriculum updates and self-reported usefulness of vocational training

We use the 1979, 1986, 1992, 1999, 2006, 2012, and 2018 waves of the Qualification and Career Survey (QCS) to study vocationally trained workers' self-reported usefulness of their training for their current work tasks: this is an inverse measure of skill mismatch between the training curriculum and actual work demands. The data also contain questions on workers' training occupation and their training year, implying we can assign workers to their training vintages.[47]

We regress self-reported training usefulness on the number of years since the curriculum was last updated at the time of training:[48]

$$\text{Usefulness}_{ij\tau t} = \beta \, \text{Years since update}_{j\tau} + \gamma_{\tau t}[+\rho X_j + \lambda_j] + \varepsilon_{ij\tau t} \tag{B3}$$

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. This is reported on a scale from 0 to 100 with 100 being most useful. The average usefulness is 73.[49]

The independent variable of interest is Years since update$_{j\tau}$, which measures how many years ago training occupation j received an update to its curriculum at the time the worker started vocational training. As controls, we add QCS survey wave by training completion year fixed effects ($\gamma_{\tau t}$), which also control for differences in respondent labor market experience at the time of the survey; training firm size categories (X_j) to capture any differences in training quality related to firm size; and KldB occupation fixed effects (λ_j) at either one- or four-digit level of detail. Standard errors are clustered by training occupation.

Table B10 shows the results, progressively adding controls across columns. We find a robust, statistically significantly negative correlation: this indicates that vocationally trained workers report finding their training more useful for their jobs when they have been trained in a more recently updated training curriculum. In the most saturated specification in column 4, being trained in a 15 years old curriculum (the average time for a curriculum update to occur) compared to being trained in a just updated curriculum is associated with a reduction in the reported usefulness of the training by $0.41 \times 15 = 6.2$ percentage points, corresponding to $6.2/34.1 \times 100 = 18\%$ of a standard deviation in the reported usefulness.

[47] Depending on the survey wave, training occupations are partly reported at aggregate levels, and the occupational training classification changes over time: we discard the 50% of observations where multiple curricula exist that are updated at different times within the same occupation. We focus on workers in West Germany that finished their vocational training at most 10 years prior. Whenever information on more than one vocational training is reported, we focus on the first vocational training.

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

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

Table B10: 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. $N = 6,854$. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

B.4 Curriculum change in the United States

We use Classification of Instructional Programs (CIP) data from the National Center for Education Statistics (NCES) to document the emergence of new educational degree programs in the United States over 1990–2020. CIP data systematically catalog all post-secondary degree programs in the United States, classified by field codes. Its first edition dates back to 1980, with revisions occurring in 1985, 1990, 2000, 2010 and 2020. From 1990 onward, separate records of newly added programs are available, which we also use here.

Specifically, we construct the share of newly added programs by broad field for each edition from 1990 onward, cumulating the new degree program counts over time. We then construct the share of new programs by field as the number of newly added programs over the total number of programs by field in 2020. The resulting Figure B7 highlights substantial curriculum change across a wide range of fields.

Figure B8 shows that curriculum change is common across the occupational wage spectrum, by crosswalking CIP degree fields to SOC occupation codes using the NCES-provided crosswalk and combining it with BLS Occupational Employment and Wage Statistics (OEWS) Survey data. For example, while high-paid occupations like legal professionals and computer and information sciences have seen a high share of new education programs, so have public administration and social service professions, engineering technicians, construction trades, mechanics and repair technicians, and personal and culinary services. There has been less educational content change in fields like history, and precision production.

Figure B7: U.S. Curriculum Change by Degree Field, 1990—2020

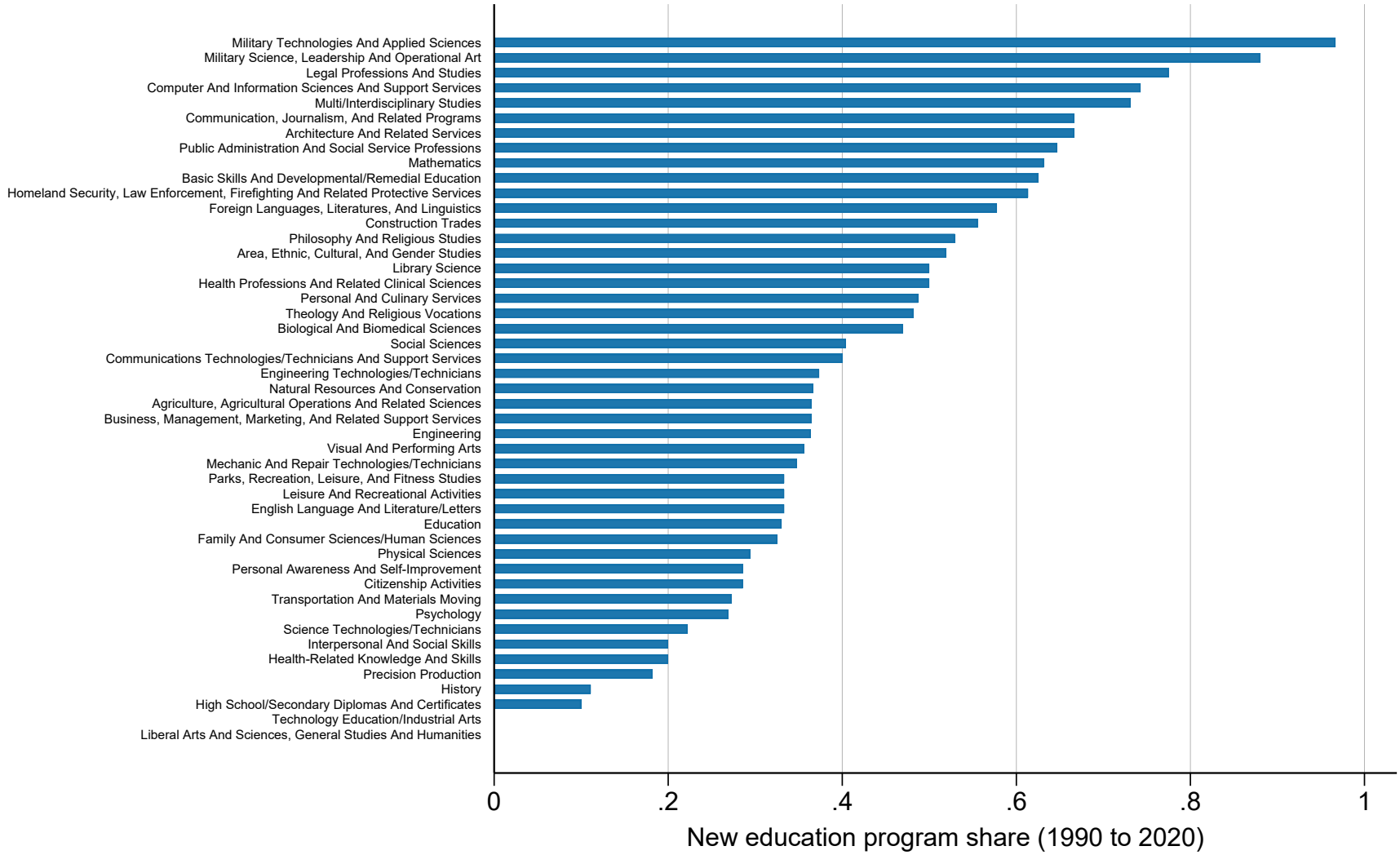


Figure plots the share of newly added degree programs by field based on CIP data.

Figure B8: U.S. Curriculum Change by Occupation, 1990—2020

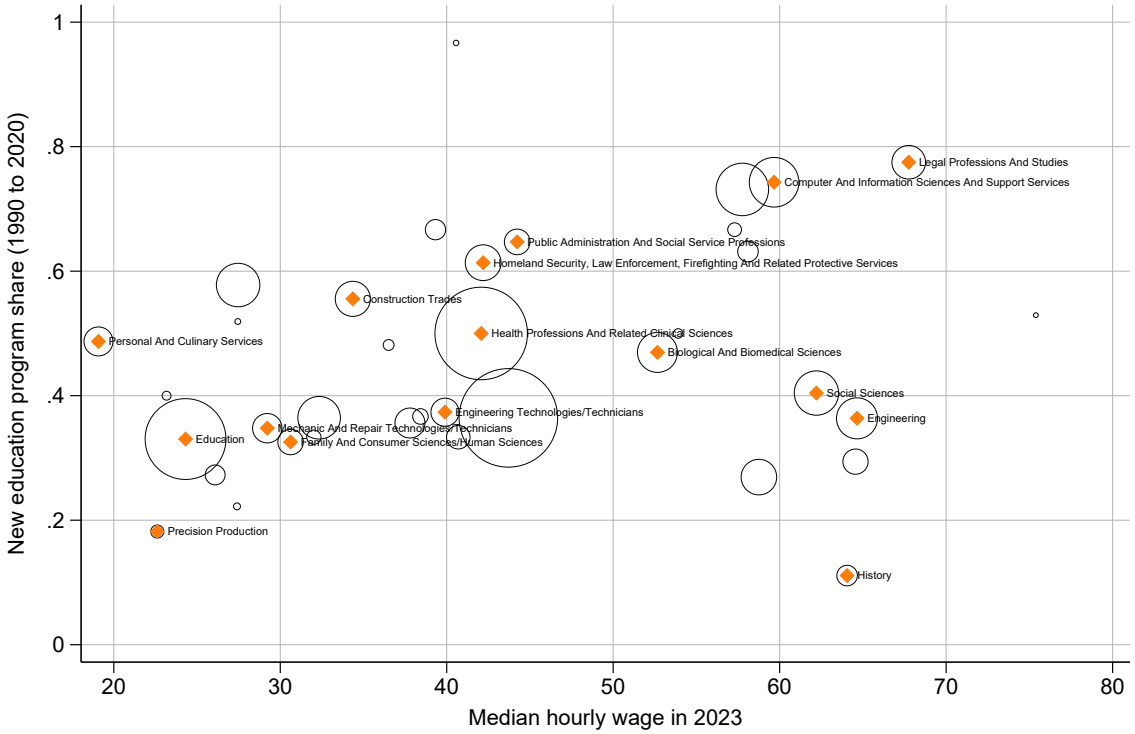


Figure plots the share of newly added degree programs by occupations ranked by median hourly wages, based on CIP data crosswalked to BLS data. The size of the circles reflects 2023 occupational employment shares.

C Labor market impacts

C.1 Entrants' on-the-job computer technology use

As in Appendix B.3, we use German Qualification and Career Survey (QCS) data, a worker survey which includes questions on technology use. The analyses in this appendix use the same difference-in-differences design we implement to study labor market impacts in Section 4.2: methodological details and discussion can be found there. We compare outcomes for cohorts of entrants trained under old curricula and cohorts of entrants trained under new curricula in occupations with training updates against entrant outcomes in occupations where no such update occurred around the same time.

We estimate:

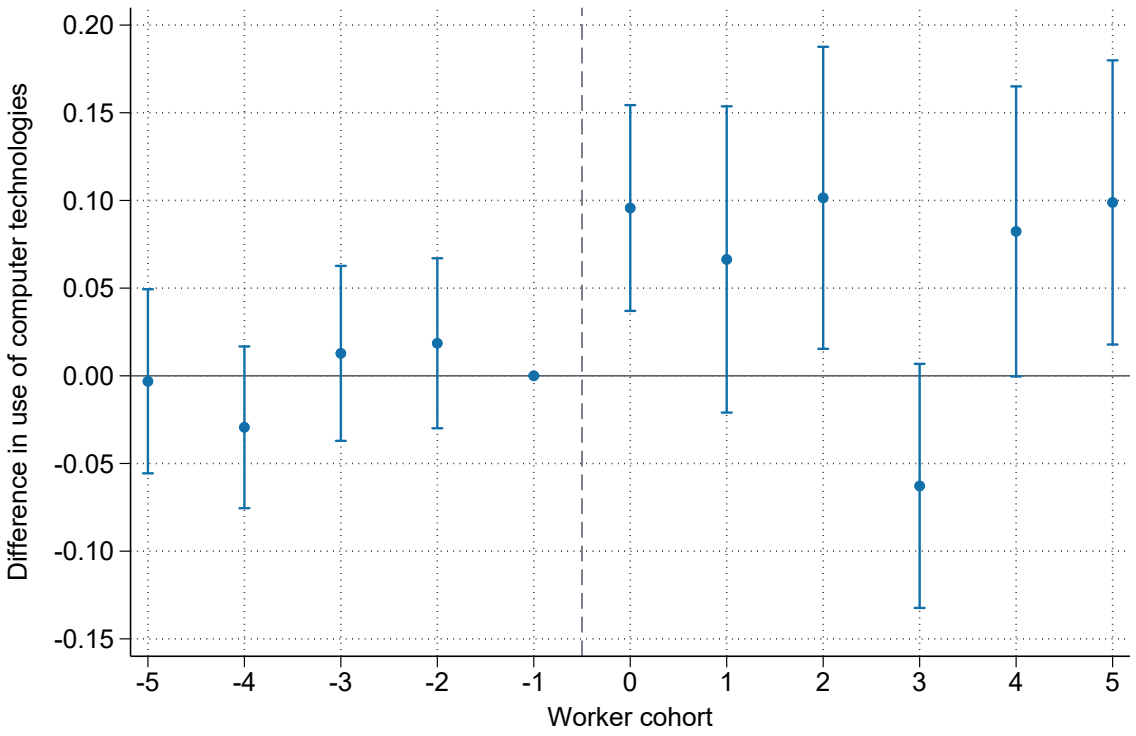
$$Y_{ijte} = \sum_{\substack{c=-5 \\ c\neq -1}}^{5} \beta_c \, \text{Update}_{je} \times I_{ce} + \sum_{c} \alpha_c I_{ce} + \delta_{je} + \gamma_{te} + \mu_e X_{it} + \varepsilon_{ijte} \ , \tag{C1}$$

where Y_{ijte} is an outcome for entrant i who has been trained in occupation j, observed in calendar year t within event e, and X_{it} includes prior school education, gender, and event time $\times$ year to control for the fact that respondents may have vastly differ in their times since training.

As an outcome, we consider entrants' self-reported on the job use of computers and computer-controlled machines, following Arntz et al. (2025): this is a binary variable with a mean of 0.31. Figure C1 shows that computer technology use generally increases due to curriculum updates by approximately 10 percentage points, i.e. 30%. This is also consistent with results in Appendix E, which shows that firms increase capital investments when they are exposed to updated vocational training.

Table C1 shows results separately for low and high technology-exposed curriculum updates, in separate samples in columns 1 and 2, and in the full sample with an interacted specification in column 3. This shows that computer use is significantly more strongly rising among new-skilled entrants when the update had high technology exposure; for low-exposure events, there is no statistically significant effect on computer use.

Figure C1: Curriculum updates and changes in use of computer technologies



Stacked difference-in-differences estimates of equation (3), and 95% confidence intervals. The dependent variable is workers' self-reported on the job use of computers and computer-controlled machines, based on QCS data from all available waves (1979, 1986, 1992, 1999, 2006, 2012, 2018). Based on 54 curriculum update events. $N = 47,599$. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table C1: Curriculum updates and changes in use of computer technologies by technology exposure

	Low technology exposure	High technology exposure	Full sample
	(1)	(2)	(3)
Post × Treated	0.05	0.14***	0.05
	(0.03)	(0.04)	(0.03)
Post × Treated × High technology exposure			0.09*
			(0.05)
N	28281	16629	44910

C.2 Entrants

Table C2: Descriptives of Vocationally Trained Labor Market Entrants, Stacked Sample

	A. Treated			*B. Control*		
	Mean	SD	Median	Mean	SD	Median
Age	24.08	2.78	24.00	24.15	2.97	24.00
Year of birth	1978	8.16	1976	1978	8.35	1978
Female	0.33	0.47	0.00	0.50	0.50	1.00
Average daily wage (euros)	75.69	30.63	75.49	72.61	30.88	72.03
Annual daily wage growth	0.04	0.43	0.04	0.04	0.42	0.04
Annual days employed	262	145	365	264	143	365
Annual labor earnings (euros)	20,326	14,795	21,972	19,678	14,476	20,977
Firm size	642	2,734	53	422	2,066	40
Job mobility, relative to apprenticeship:						
Occupation	0.43	0.49	0.00	0.38	0.49	0.00
Industry	0.47	0.50	0.00	0.43	0.49	0.00
Firm	0.64	0.48	1.00	0.66	0.47	1.00
Job mobility, year-to-year:						
Occupation	0.18	0.39	0.00	0.17	0.37	0.00
Industry	0.18	0.38	0.00	0.17	0.37	0.00
Firm	0.25	0.43	0.00	0.25	0.44	0.00
N unique workers	42,815			102,516		

SIEED sample, dataset stacked in event time as described in Section 4.1, for worker cohort $\tau = -1$. 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. Annual daily wage growth is the log daily wage change across years.

Figure C2: Cohort Coefficients for Treated and Control Group Entrant Workers

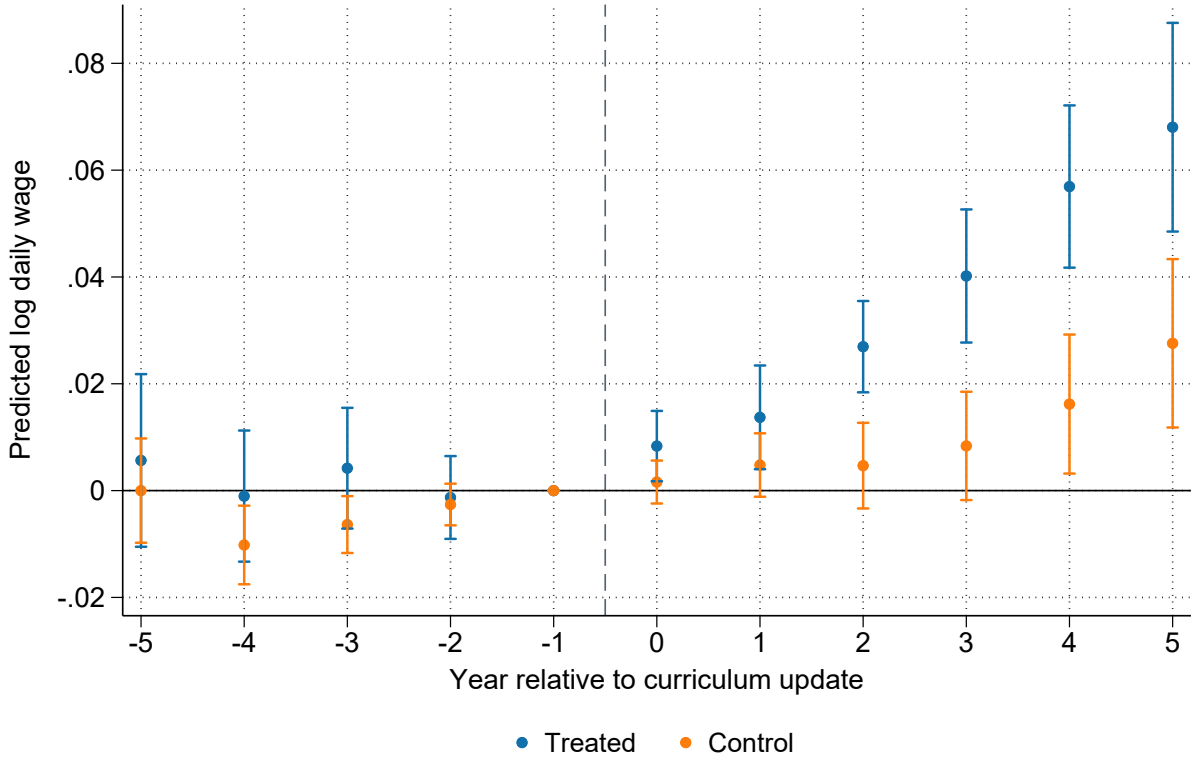
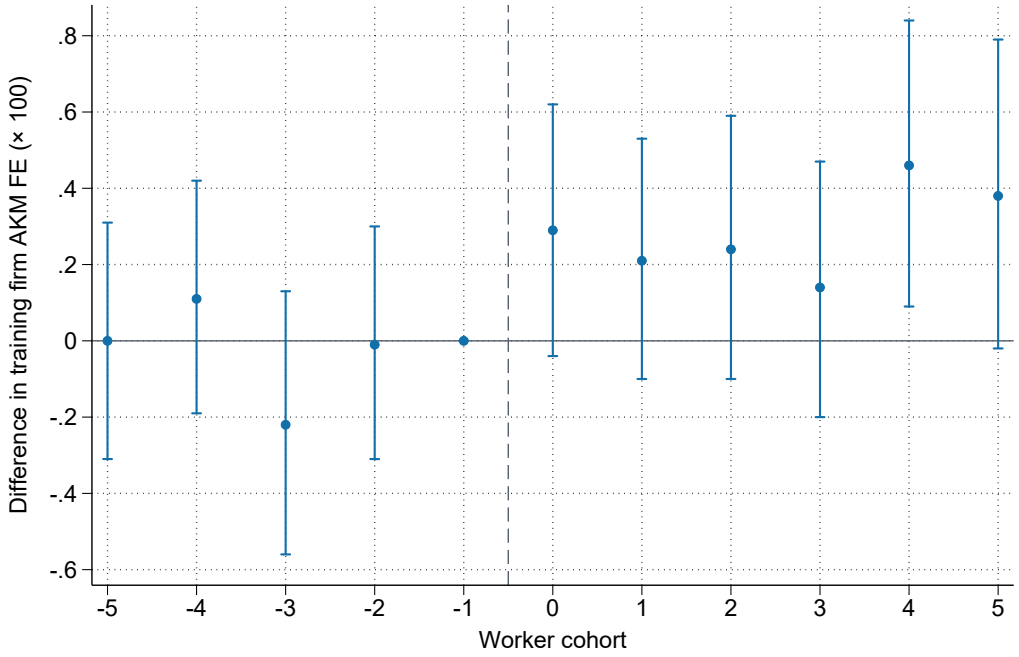


Figure reports cohort coefficients for treated ($\alpha_c + \beta_c$) and control group workers (α_c) using the stacked difference-in-differences estimate of equation (3) for log daily wages. To net out a common linear trend, we subtract a linear trend anchored at $c = -1$ for both treated and control 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.

Figure C3: Impacts of Curriculum Updates on Training Firm Composition

A. Training Firms' AKM Fixed Effects



B. Daily Wages Net of Training Firms' AKM Fixed Effects

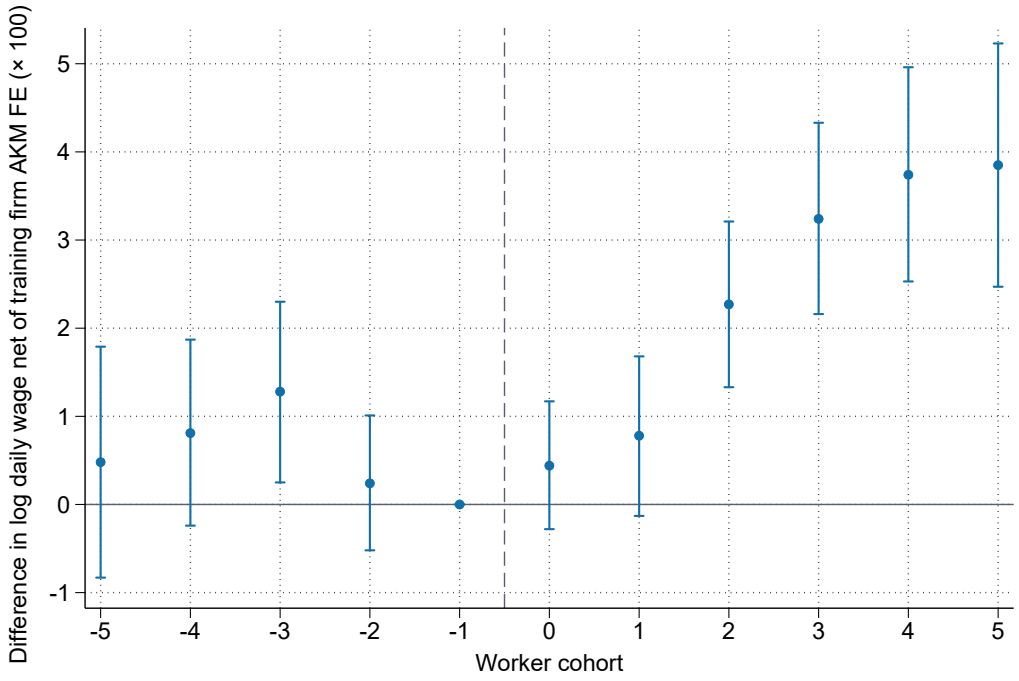


Figure reports stacked difference-in-differences estimates of equation (3), and 95% confidence intervals; estimated separately by year post training. Cohort 0 is the first cohort with the new curriculum; cohort -1 is the reference category. Standard errors clustered at the level of occupation by event. Panel B: the specification subtracts the AKM fixed effect of workers' training firms (also constructed from log daily wages). Panel A: $N = 2,193,797$; Panel B: $N = 8,831,369$; 357 events for both panels.

Figure C4: Impact of Curriculum Updates on Entrant Annual Income by Technology Exposure

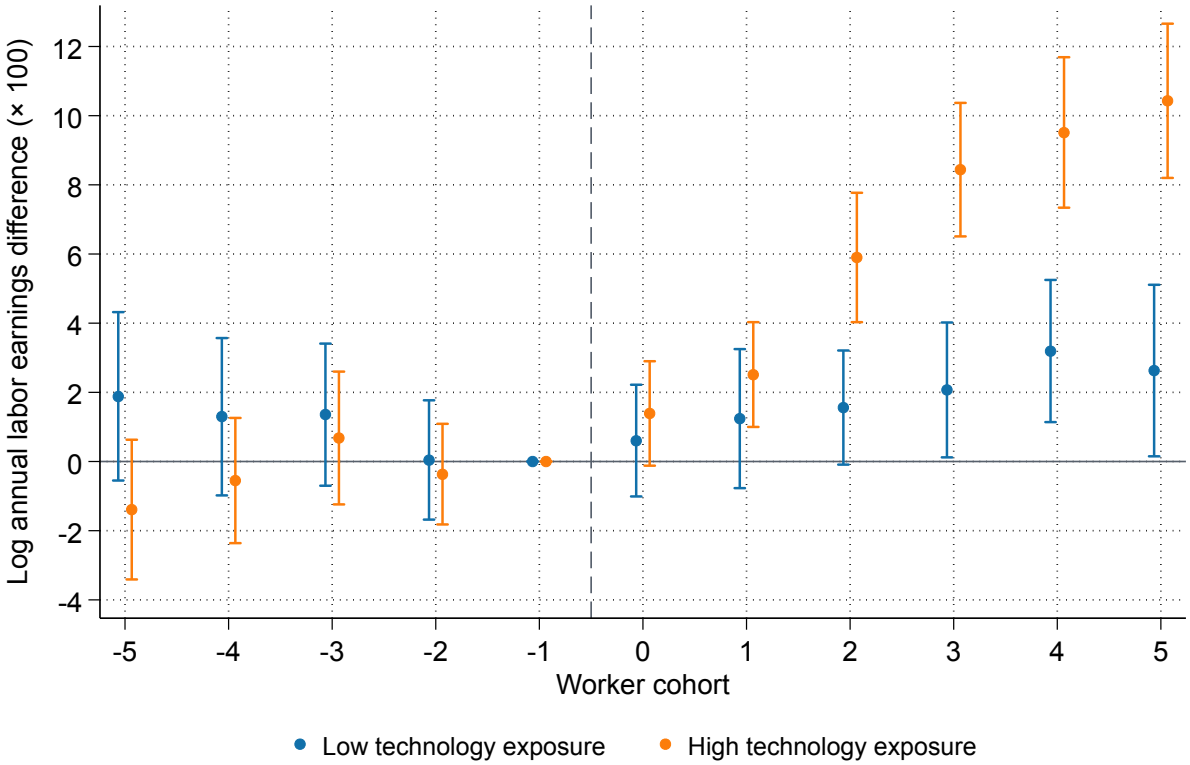
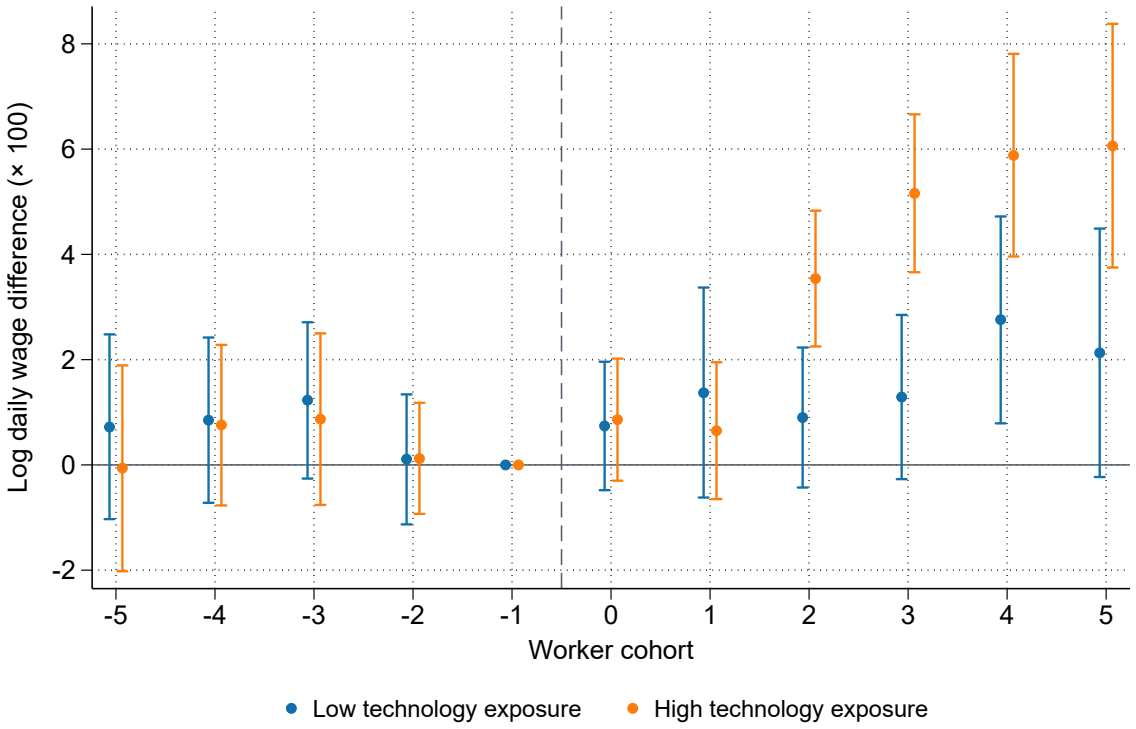


Figure reports stacked difference-in-differences estimates of equation (3), and 95% confidence intervals. Cohort 0 is the first cohort with the new curriculum; cohort -1 is the reference category. Individuals are included up to five years after graduation. Standard errors clustered at the level of occupation by event. $N = 4,253,227$ for high exposure (182 events), and $N = 4,715,806$ for low exposure (175 events).

Figure C5: Entrant Wage Impacts of Curriculum Updates by Technology Exposure, Controlling for Prior-Curriculum Technology Exposure



Stacked difference-in-differences estimates of equation (3), 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. For each cohort, technology exposure is defined as the log number of time-varying (lagged) digital breakthrough patents linked to the occupation's pre-update curriculum. $N = 4,241,611$ for low exposure (175 events), and $N = 4,049,817$ for high exposure (182 events).

Figure C6: Entrant Log Daily Wage Impacts of Curriculum Updates By Post-Training Year

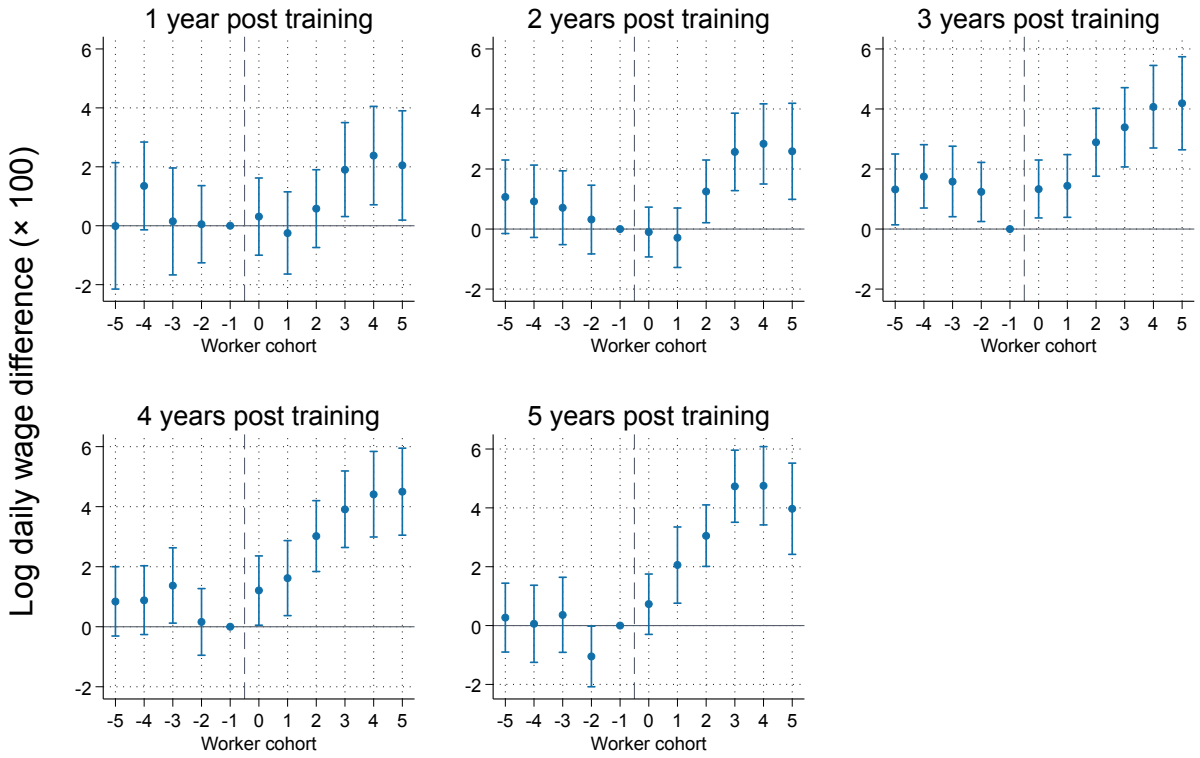


Figure reports stacked difference-in-differences estimates of equation (3), and 95% confidence intervals; estimated separately by year post training. Cohort 0 is the first cohort with the new curriculum; cohort -1 is the reference category. Standard errors clustered at the level of occupation by event. 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 C7: Entrant Log Daily Wage Impacts of Curriculum Updates By Post-Training Year and Technology Exposure

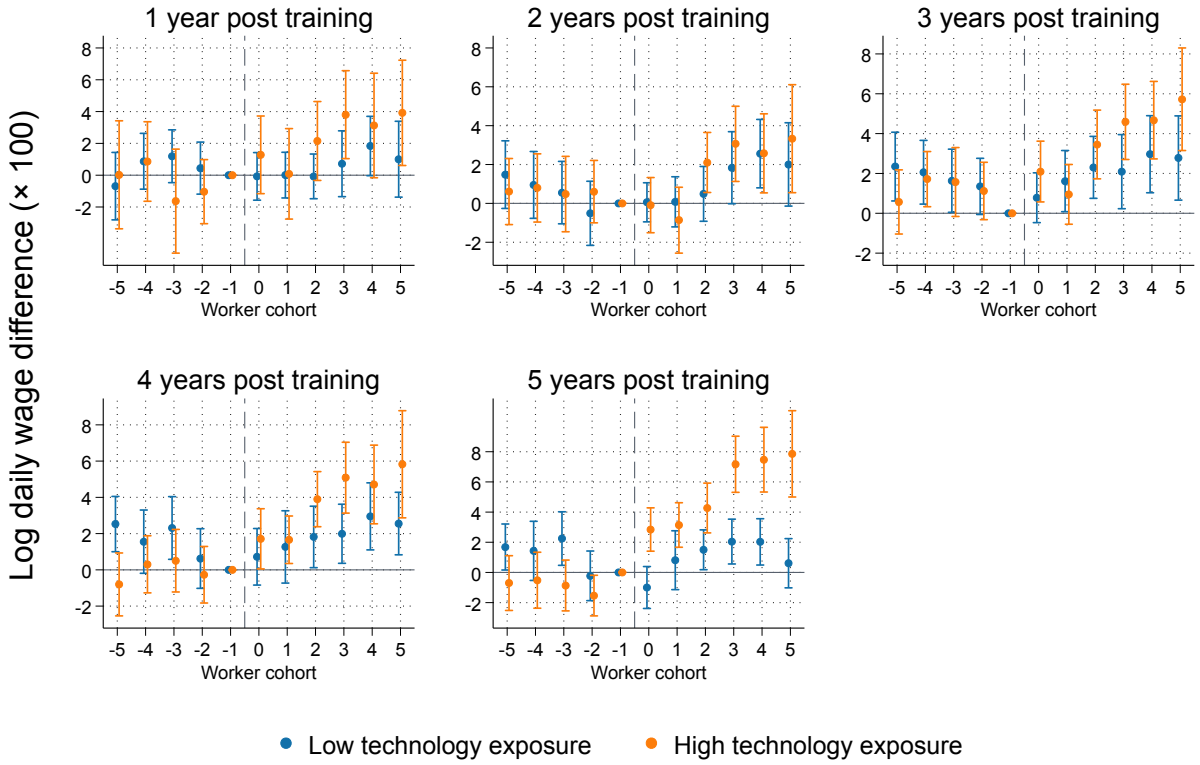
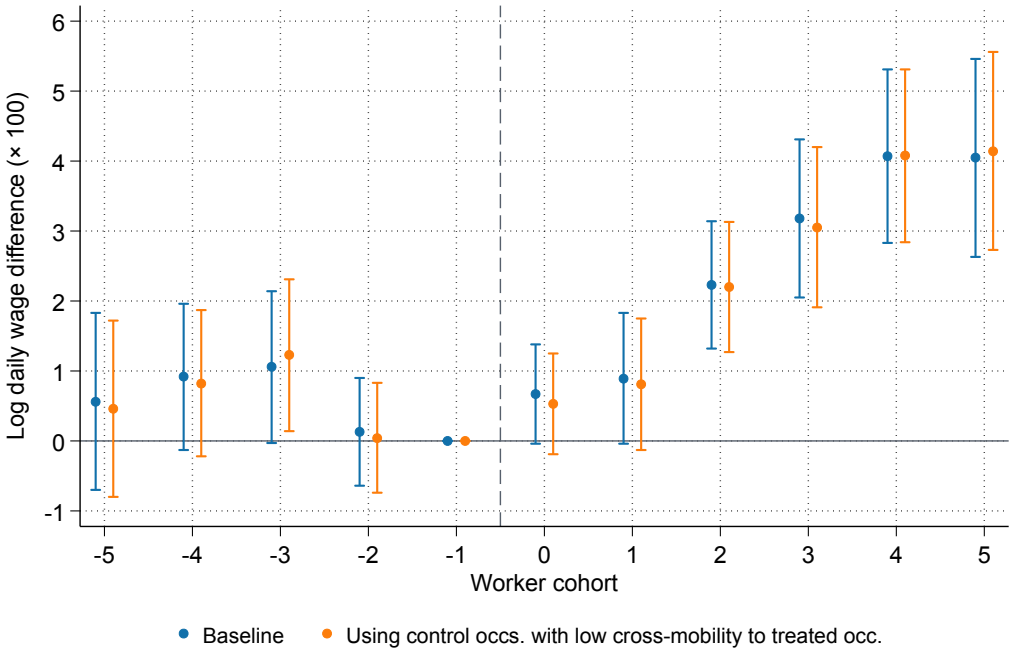


Figure reports stacked difference-in-differences estimates of equation (3), and 95% confidence intervals; estimated separately by year post training. For example, the series labeled '5 years post training' shows how log daily wages in the fifth year after vocational training completion evolve across 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 C8: 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

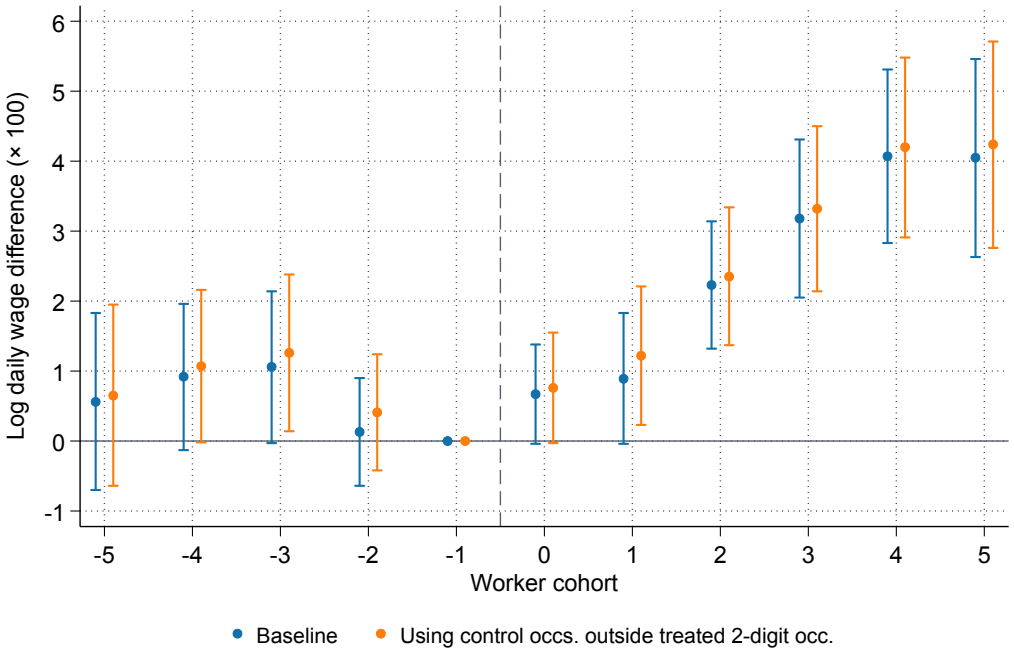
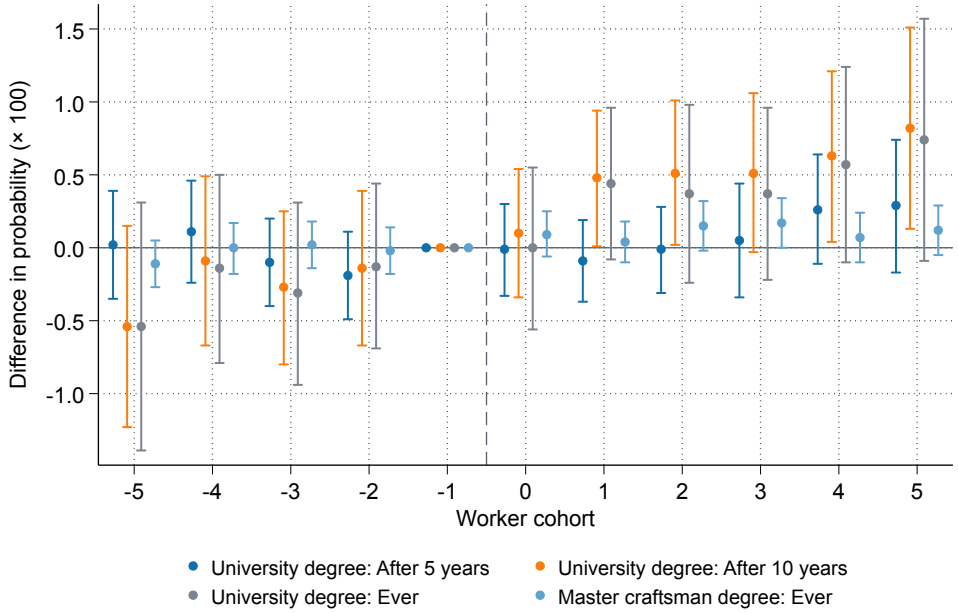


Figure reports stacked difference-in-differences estimates of equation (3), and 95% confidence intervals. Cohort 0 is the first cohort with the new curriculum; cohort -1 is the reference category. Individuals are included up to five years after graduation. Standard errors clustered at the level of occupation by event. Both panels based on 357 events. Panel A: $N = 8,913,473$; Panel B: $N = 5,621,395$.

Figure C9: 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

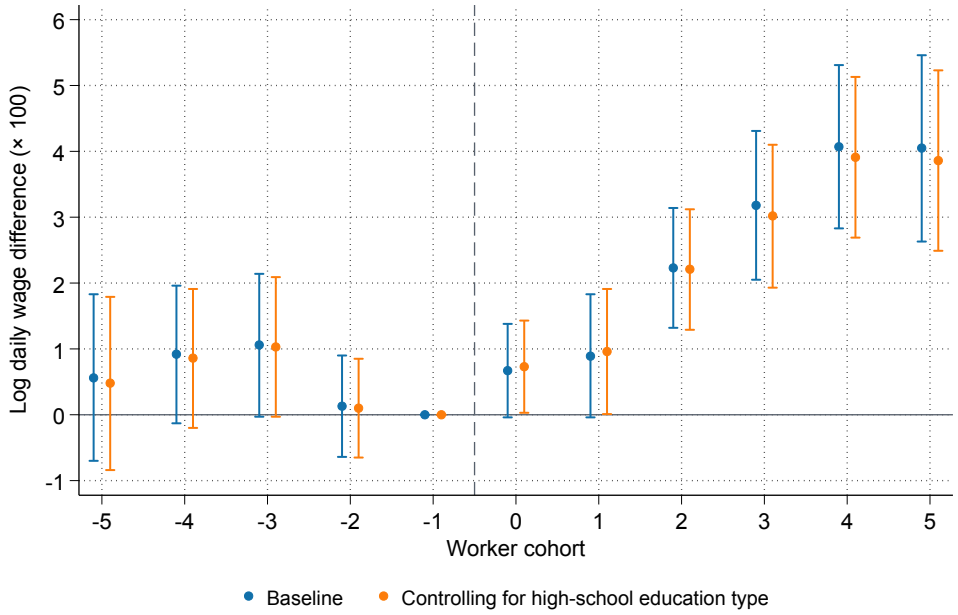
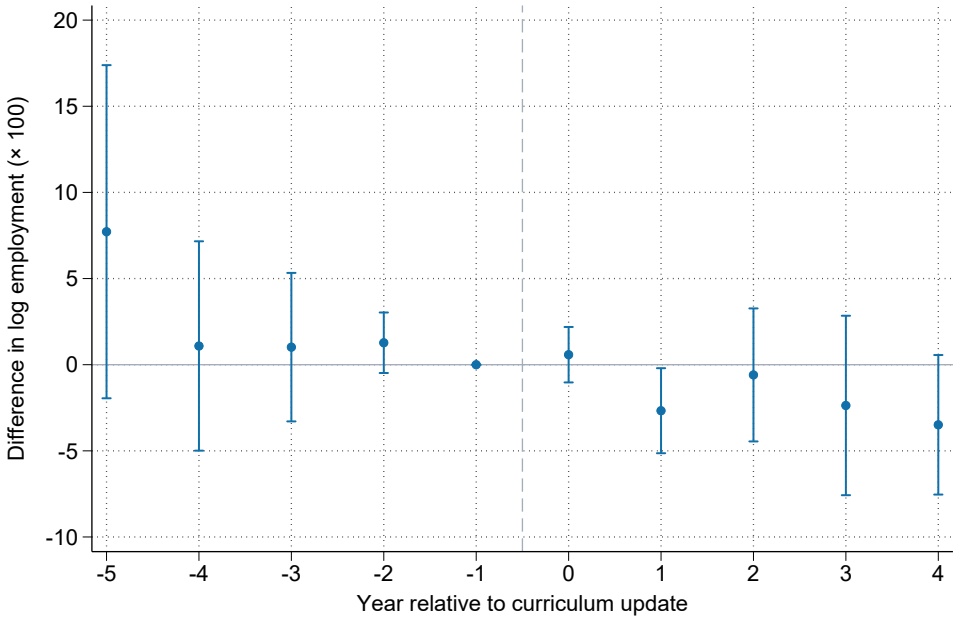


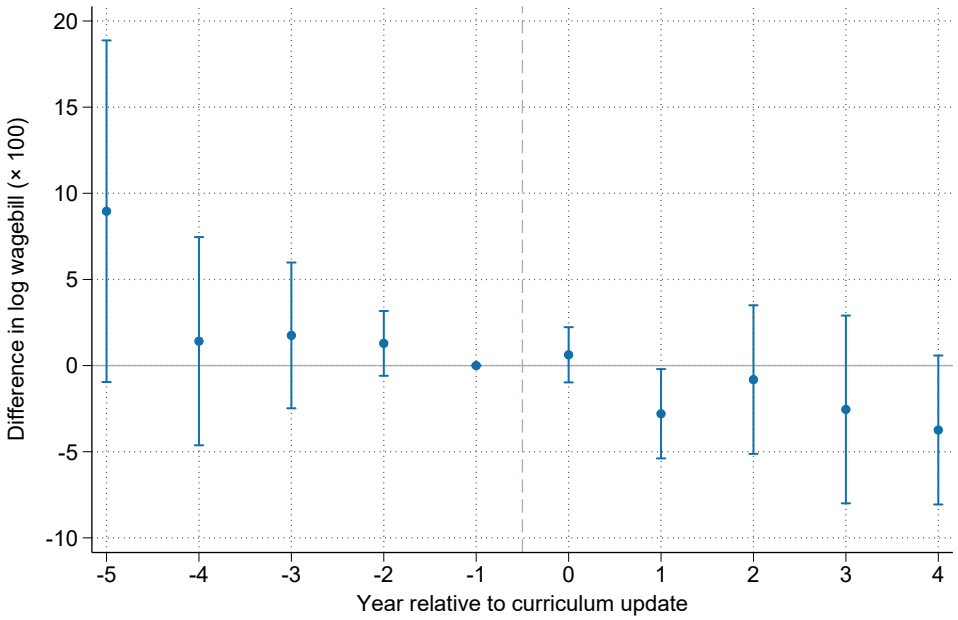
Figure reports stacked difference-in-differences estimates of equation (3), and 95% confidence intervals; estimated separately by year post training. Cohort 0 is the first cohort with the new curriculum; cohort -1 is the reference category. Standard errors clustered at the level of occupation by event. Based on 357 events for both panels; $N = 2,232,166$ for panel A; $N = 8,969,021$ for panel B.

Figure C10: Occupational Total Employment and Wagebill around Curriculum Updates

A. Log Total Employment



B. Log Total Wagebill



Stacked difference-in-differences estimates of curriculum updates on occupational total full-time log employment (Panel A) and occupational total full-time log wagebill (Panel B), comparing occupations with curriculum updates to occupations without updates. Based on 248 events for both panels. Panel A: $N = 27,452$; Panel B: $N = 27,452$. The first year with the new curriculum is 0. Models absorb occupation-by-event dummies, calendar year-by-event dummies and time-to-event dummies. Standard errors are clustered at the curriculum level. Considering full-time employed workers in employment subject to social security contributions.

C.3 Incumbents

Table C3: Descriptives of Occupational Incumbents, Stacked Sample

	A. Treated			*B. Control*		
	Mean	SD	Median	Mean	SD	Median
Age	43.40	8.60	43	44.21	8.52	44
Year of birth	1958	11	1959	1957	11	1958
Female	0.30	0.46	0.00	0.33	0.47	0.00
Average daily wage (euros)	108.96	50.11	103.11	112.02	52.87	103.59
Annual daily wage growth	0.01	0.16	0.01	0.01	0.17	0.01
Annual days employed	362	20	365	361	22	365
Annual labor earnings (euros)	39,477	18,407	37,405	40,488	19,463	37,535
Firm size	840	3,281	90	912	3,483	109
Job mobility (year-to-year):						
Occupation	0.09	0.29	0.00	0.07	0.26	0.00
Industry	0.07	0.26	0.00	0.05	0.22	0.00
Firm	0.11	0.31	0.00	0.09	0.29	0.00
N unique workers		710,926			596,398	

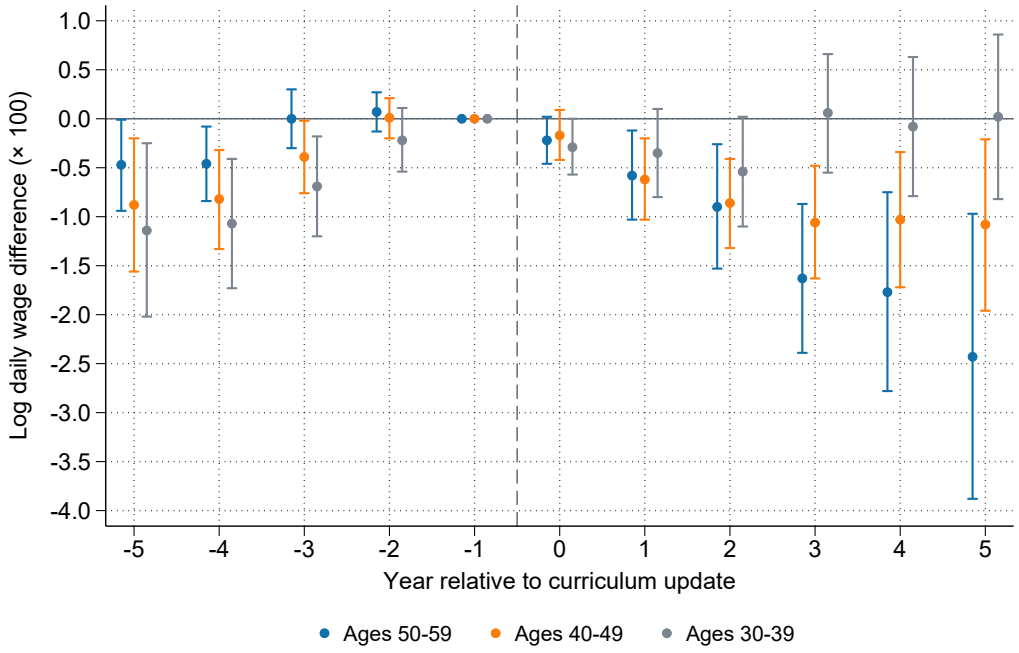
For years $\tau = -1$, except mobility outcomes which are measured over the entire post-treatment period.

Table C4: Descriptives of Occupational Incumbents by Age Group, Stacked Sample

	A. Treated			*B. Control*		
	Mean	SD	Median	Mean	SD	Median
			A. Age 50-59			
Age	52.83	2.77	53	52.87	2.77	53
Year of birth	1951	1952	1952	1950	1952	1952
Female	0.34	0.47	0.00	0.34	0.47	0.00
Average daily wage (euros)	109.27	55.28	102.86	114.33	57.77	104.49
Annual daily wage growth	0.00	0.16	0.00	0.01	0.17	0.01
Annual days employed	362	365	365	360	365	365
Annual labor earnings	39,570	37,254	37,254	41,302	37,829	37,829
Firm size	749	91	91	853	107	107
Job mobility (year-to-year):						
Occupation	0.09	0.29	0.00	0.07	0.26	0.00
Industry	0.06	0.23	0.00	0.04	0.20	0.00
Firm	0.09	0.29	0.00	0.07	0.26	0.00
N unique workers		230,351			207,357	
			B. Age 40-49			
Age	43.42	2.86	43	43.51	2.85	44
Year of birth	1958	1960	1960	1958	1960	1960
Female	0.31	0.46	0.00	0.34	0.47	0.00
Average daily wage (euros)	110.66	52.49	104.70	113.64	54.47	105.25
Annual daily wage growth	0.01	0.15	0.01	0.01	0.16	0.01
Annual days employed	362	365	365	361	365	365
Annual labor earnings (euros)	40,130	38,008	38,008	41,131	38,170	38,170
Firm size	853	92	92	943	116	116
Job mobility (year-to-year):						
Occupation	0.10	0.30	0.00	0.08	0.26	0.00
Industry	0.07	0.25	0.00	0.05	0.22	0.00
Firm	0.11	0.31	0.00	0.09	0.28	0.00
N unique workers		328,704			270,184	
			C. Age 30-39			
Age	33.75	2.85	34	33.92	2.85	34
Year of birth	1965	1965	1965	1965	1965	1965
Female	0.27	0.44	0.00	0.33	0.47	0.00
Average daily wage (euros)	107.33	41.88	102.24	107.51	43.53	101.37
Annual daily wage growth	0.02	0.16	0.01	0.02	0.18	0.02
Annual days employed	362	365	365	360	365	365
Annual labor earnings (euros)	38,877	37,120	37,120	38,830	36,749	36,749
Firm size	942	90	90	981	105	105
Job mobility (year-to-year):						
Occupation	0.09	0.29	0.00	0.07	0.25	0.00
Industry	0.08	0.28	0.00	0.06	0.25	0.00
Firm	0.13	0.33	0.00	0.11	0.31	0.00
N unique workers		300,128			220,183	

For year $\tau = -1$, except mobility outcomes which are measured over the entire post-treatment period.

Figure C11: Wage Impacts of Curriculum Updates for Occupational Incumbents, Controlling for Prior-Curriculum Technology Exposure



Stacked difference-in-differences estimates of equation (4), and 95% confidence intervals. For each cohort, technology exposure is defined as the log number of time-varying (lagged) digital breakthrough patents linked to the occupation's pre-update curriculum. Based on 419 curriculum update events, $N_{50-59} = 3,074,913$, $N_{40-49} = 4,735,178$, $N_{30-39} = 4,242,592$.

D Curriculum updates and trainee composition

Curriculum change is in principle observable to prospective students (and their parents): curricula are publicly available legal documents, and the Federal Institute for Vocational Education and Training (BIBB) also communicates training updates, which in recent decades includes posting these changes on its website. This raises the concern that the quality of student intake may change as a direct result of curriculum updates, violating parallel trends—if student quality improves, this could contribute to the positive wage effects we find. On the other hand, if student quality worsens, our estimates may understate the returns to skill upgrades contained in the new curricula.

We use two separate datasets (DAZUBI and official apprenticeship market statistics) containing training occupation-level information on apprenticeships and trainees, obtained from the BIBB, to consider how trainee observables evolve around curriculum updates. We use a stacked DiD design as before, comparing apprenticeship position numbers and trainee observables before and after curriculum updates in training programs which were updated versus those that were not.[50] The estimating equation is

$$Y_{jte} = \sum_{\substack{\tau=-5 \\ \tau\neq-1}}^{5} \beta_\tau \text{Update}_{je} \times I_{\tau e} + \delta_{je} + \gamma_{te} + \varepsilon_{jte}, \tag{D1}$$

where Y_{jt} is a training occupation-level outcome for training occupations j in year t. Because we stack observations as before, j indexes training occupations by curriculum update ('event'), and t indexes calendar years by event. τ denotes calendar years relative to the year of the potential curriculum change event: we normalize $\tau = 0$ as the first calendar year the curriculum is updated. We control for training occupation dummies and calendar year dummies, each interacted with event dummies. Standard errors are clustered at the training occupation by event level, as before. Table D1 shows descriptives of the DAZUBI dataset, using values in the initial period $\tau = -5$.

We estimate models for West-Germany over 1976–2022. A first set of results reported in panel A of Figure D1 describes the apprenticeship positions: the number of training contracts, the share of these terminated before the end of training[51], the pass rate among contracts surviving until the final exam, the share of positions remained unfilled, and the share of unsuccessful applicants. We find that the number of apprenticeship positions increases for updated curricula compared to those without updates, with a transitory dip in enrollment the year before the curriculum update. The share of terminated apprenticeship contracts does not change following curriculum updates: updated programs have a slightly

[50] We exclude curriculum updates that regrouped several training occupations into several other training occupations without a clear correspondence between the previous and succeeding training occupations.

[51] Such terminations occur when students choose to dis-enroll (and potentially re-enroll in a different program).

higher termination rate although these estimates are small and never statistically significant. Exam pass rates (shifted by the standard apprenticeship length of three years to align $t = 0$ with the pass rate of the first new-skilled training cohort) are unaffected. We also do not observe changes in the share of unfilled apprenticeship positions (labeled 'excess supply of positions' in Figure D1) or unsuccessful apprenticeship applications (labeled 'excess demand by apprentices') around curriculum updates that would hint at altered interest in training occupations following an update.

Panel B of Figure D1 considers changes in the composition of trainees by gender, age, and education. Overall, we find little evidence that curriculum updates coincide with changes in these trainee characteristics. The gender and age composition of trainees in updated programs evolves in the same way as in programs without updates. Moreover, curriculum updates do not coincide with changes in the educational composition of trainees' high school diploma[52]: we consider the share of students with an upper school track (the highest high school diploma), a middle school track, a lower school track, and no high school diploma, finding no discernible trend changes for any of these. Further, Figure D2 shows estimates separately for production and service training occupations, showing these findings hold within these subsamples also.

All in all, we do not find evidence to support changes in worker composition concurrent with curriculum change. This bolsters confidence that the documented wage returns from curriculum reform are the result of skill upgrading rather than reflecting a changing worker worker selection into updated training programs.[53]

[52] Because of changes in the educational classification, we estimate these effects separately over 1976–2006 and 2007–2022.

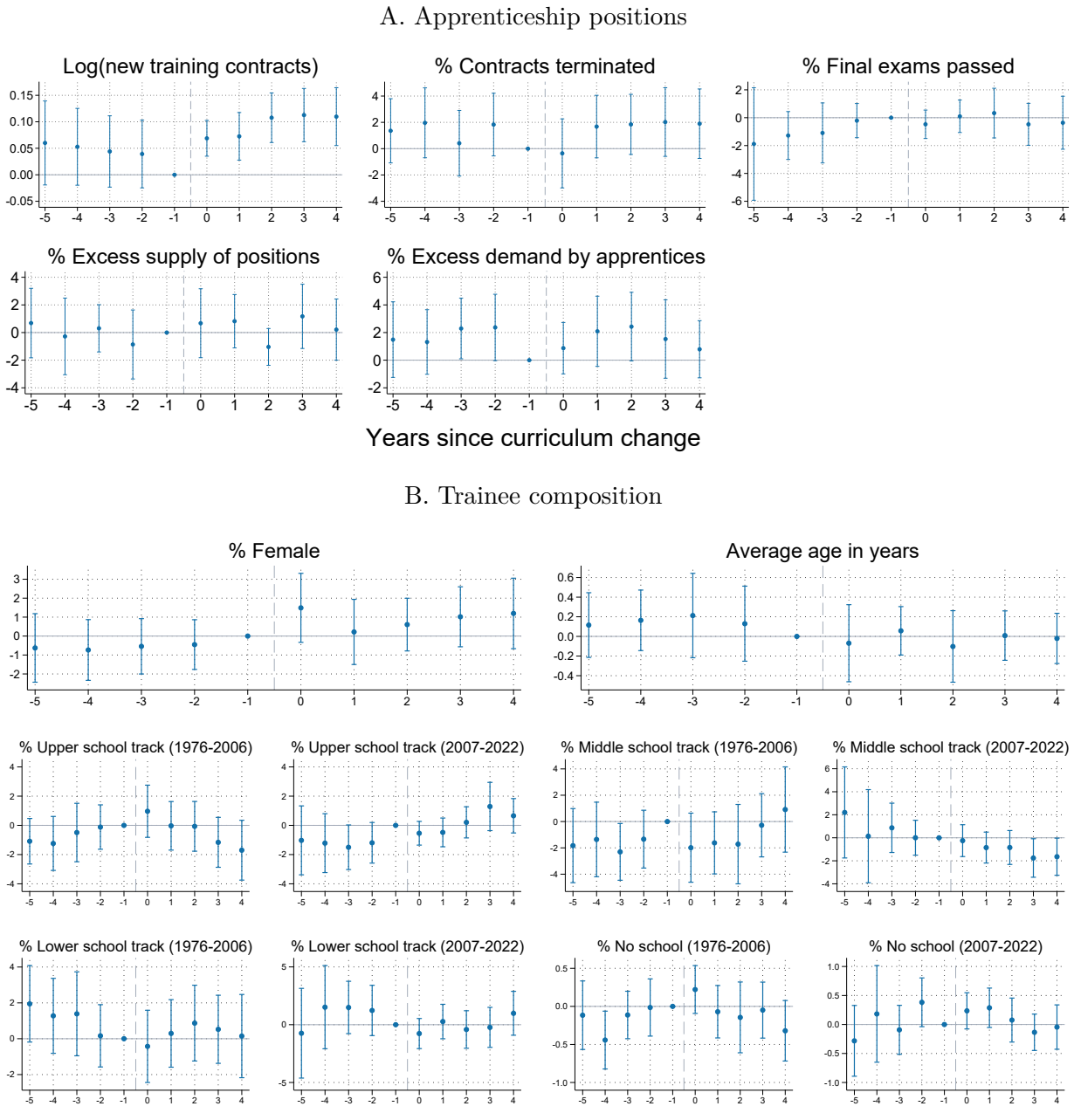
[53] Along with no changes in trainee composition, we also do not find any changes in *total* employment or wagebills for training occupations around curriculum update events, using SIAB data. Estimates for these models are shown in Figure C10, highlighting that training occupations with updated curricula are on similar employment and wagebill trajectories as training occupations without curriculum updates over the same time period.

Table D1: Descriptives on Apprenticeship Positions and Trainee Composition

	Mean	SD	N
A. Apprenticeship positions, supply, and demand			
Log(new training contracts)	5.79	2.04	33,666
% Contracts terminated	20.64	13.85	32,689
% Final exams passed	89.3	8.3	9,377
% Excess supply of positions	4.19	5.19	7,869
% Excess demand by apprentices	10.86	11.12	7,869
B. Apprenticeship composition			
% Female	32.94	34.37	22,538
Average age in years	19.47	1.05	10,334
% Upper school track (1976–2006)	16.64	20.74	17,619
% Upper school track (2007–2022)	21.15	23.33	8,694
% Middle school track (1976–2006)	31.33	17.29	17,619
% Middle school track (2007–2022)	35.01	14.95	8,694
% Lower school track (1976–2006)	34.6	23.77	17,619
% Lower school track (2007–2022)	38.52	25.76	8,694
% No school (1976–2006)	1.95	3.34	17,619
% No school (2007–2022)	2.9	3.33	8,694

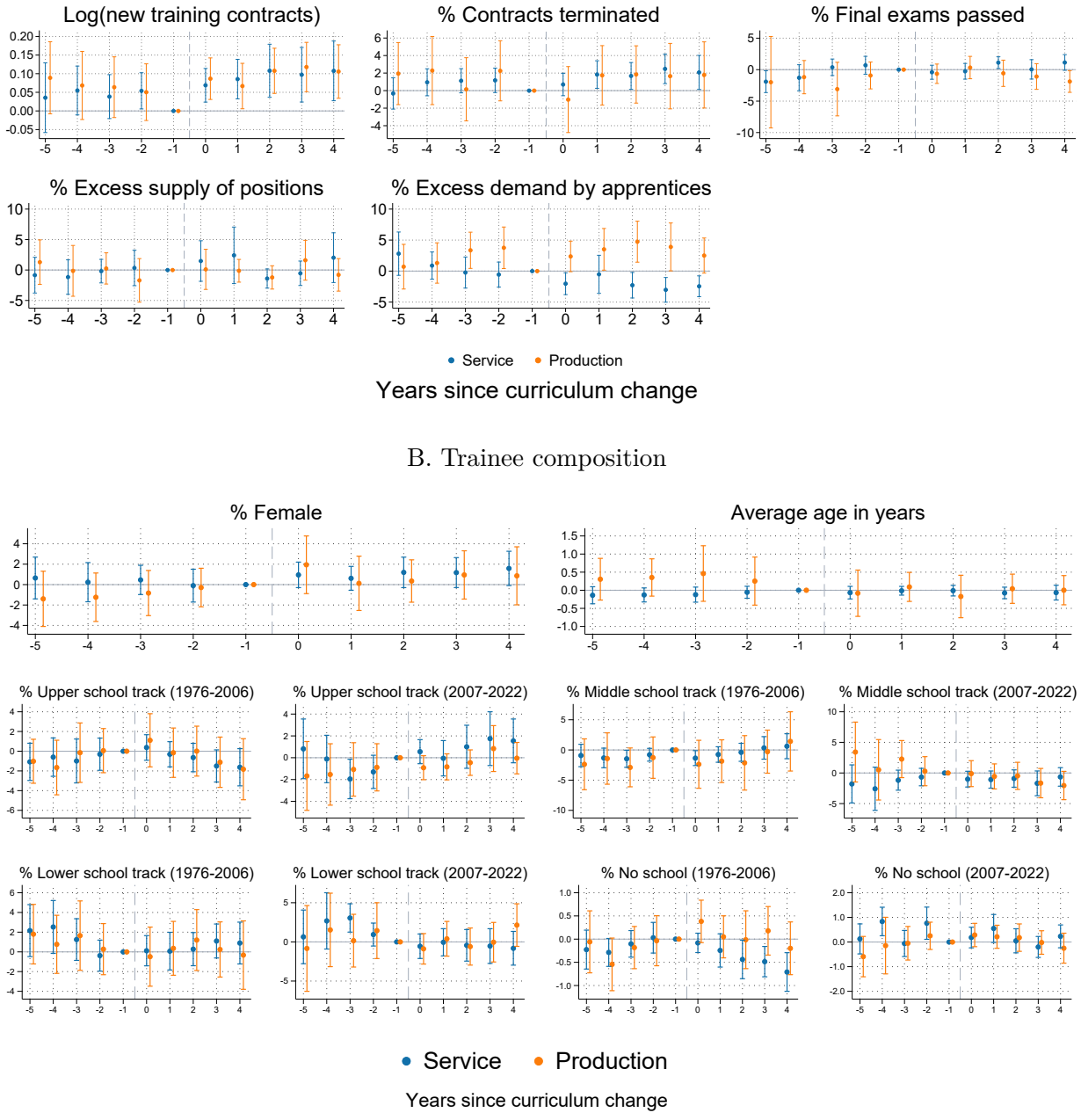
Mean and standard deviation in the initial year $\tau = -5$. N shows the number of observations included in the respective regressions: this varies across outcomes due to missing values.

Figure D1: Apprenticeship Positions and Trainee Composition Before and After Curriculum Updates



Stacked difference-in-differences estimates of curriculum updates on apprenticeship positions and trainee composition, comparing occupations with curriculum updates to occupations without updates. Based on 317 curriculum update events (pure content changes, aggregations without simultaneous segregations, and segregations without simultaneous aggregations) over 1976–2022, West Germany only, $N = 57,745$. The first year with the new curriculum is 0. Exam pass rates are shifted by the standard apprenticeship length of three years to align $t = 0$ with the pass rate of the first new-skilled training cohort. Models absorb occupation-by-event dummies, calendar year-by-event dummies and time-to-event dummies. Standard errors are clustered at the curriculum level. Excess supply of positions defined as the number of unfilled positions among all offered positions in %. Excess demand defined as the number of rejected applications by students over the number of all applications. Education shares 1976–2006 based on the previously attended school type, including both general and vocational schools. Education shares 2007–2022 based on school-leaving certificate (excluding vocational schools). Excess supply and excess demand available from 2007 onward; % final exams passed available from 2010 onward; % female available from 1993 onward; average age in years available from 2007 onward.

Figure D2: Apprenticeship Number and Composition Before and After Curriculum Updates – Production versus Service Occupations



Stacked difference-in-differences estimates of curriculum updates on apprenticeship positions and composition comparing occupations with curriculum updates to occupations without updates, over 1976–2022. Based on 223 updating events (pure content changes, aggregations without simultaneous segregations, and segregations without simultaneous aggregations) in production occupations (N=39,180) and 94 updating events in service occupations (N=18,565). The first year with the new curriculum is 0. Exam pass rates are shifted by the standard apprenticeship length of three years to align $t = 0$ with the pass rate of the first new-skilled training cohort. Models specification in equation (D1). Standard errors are clustered at the curriculum level. Excess supply of positions defined as the number of unfilled positions among all offered positions in %. Excess demand defined as the number of rejected applications by students over the number of all applications. Education shares 1976–2006 based on the previously attended school type, including both general and vocational schools. Education shares 2007–2022 based on school-leaving certificate (excluding vocational schools). Excess supply and excess demand available from 2007 onward; % final exams passed available from 2010 onward; % female available from 1993 onward; average age in years available from 2007 onward.

E Curriculum updates and firm capital investments

If curriculum updates improve workers' ability to work with new technologies, firms should increase capital investments following curriculum updates when they are more exposed the new entrants, in particular in occupations exposed to new technologies. Previous work has shown a positive correlation between firms' apprenticeship training participation and innovation in Switzerland (Rupietta and Backes-Gellner, 2019); provided causal evidence that apprentice-supply reductions reduce firm technology investments in Germany (vom Baur, 2025); and documented higher mentions of technology use in job ads for firms employing new-skilled apprentices in specific IT-intensive occupations in Switzerland (Schultheiss and Backes-Gellner, 2024). We identify causal effects of curriculum updates on investments using a difference-in-differences design that considers all observed updates, allowing us to compare those with high and low technology exposure. Examining whether firms increase investments reveals a mechanism through which curriculum updates may improve worker outcomes: enhanced capital-skill complementarity for workers with new skills.

We leverage IAB's Linked-Employer-Employee-Data (LIAB), which combines the IAB Establishment Panel survey with administrative employment information from June 30 of each year for all employees who ever work at surveyed firms, over 1975–2021. The IAB Establishment Panel is an annual representative survey of establishments containing information about investments since 1993. It is conducted at the workplace level (henceforth: firms). Employment information is based on administrative records reported to social security. We retain firms in West Germany to ensure comparability with the employment analyses. We then merge these data with our curriculum update events, and designate firms as treated if the curriculum updates for at least one of their two largest occupations (in terms of pre-update employment share).[54] Treatment thus captures that firms have a high exposure to vocationally trained labor with updated curricula.

We estimate a stacked-event DiD model at the firm level: where Y_{ft} is log investments for firm f in year t. Event time τ is normalized such that $tau = 0$ is the year trainees enter vocational training under a new curriculum. Update_f is the firm-level treatment indicator defined as above. δ_f captures firm fixed effects, and γ_τ event year fixed effects. As before, all indices refer to the index by event. We match treated and control firms on log investment levels in the pre-treatment periods ($\tau - 1$ to $\tau - 5$) using Mahalanobis distance matching (selecting the three nearest-neighbors), thereby only retaining firms observed over the five pre-treatment years. To address zero investments, we match on both log(investments+1) and binary variables for zero investments. We cluster standard errors at the event-by-firm level.

[54] When there are more than two occupations tied for largest, we consider all largest occupations.

$$Y_{fte} = \sum_{\substack{\tau=-5 \\ \tau \neq -1}}^{5} \beta_\tau \, \text{Update}_{fe} \times I_{\tau e} + \delta_{fe} + \gamma_{te} + \varepsilon_{fte},$$

where Y_{fte} is log investments for firm f in calendar year t in event e. Event time τ is normalized such that $\tau = 0$ is the year trainees enter vocational training under a new curriculum. Update_{fe} is the firm-level treatment indicator defined as above. δ_{fe} captures firm fixed effects and λ_{te} calendar year fixed effects, both interacted with event dummies.

Table E1 shows firm-level descriptives for treated and control firms in year $\tau - 1$, post matching. Our analyses are based on an unbalanced panel of 4,680 distinct firms in $\tau = -1$, with 2,372 treated. Treated firms employ an average of 270 workers (194 for control firms), and are more likely to be in the manufacturing sector. Log investments have a high standard deviation of around 2.47, reflecting that investments are lumpy. Around 74% of treated and control firm observations report positive investments, with average log investments of 5.54 annually for treatment firms and 5.34 for control firms.

Panel A of Figure E1 shows the estimates. Log investments rise in treated versus control firms in the first year apprentices are trained in the new curriculum (taking into account grace periods, as before), with investment increases of 9.3%, corresponding to 3.9% of a standard deviation. These investment increases are also observed for curriculum updates with high technology exposure, as seen in panel B of Figure E1 – while we observe only 24 low-exposure events in these data, resulting in high standard errors for this subsample, impeding interpretation of the findings. Firms may also need additional investments simply because they take on more apprentices: in Appendix D, we show that the number of apprenticeship positions increases for updated curricula compared to those without updates. Together, these patterns suggest that firms invest both because they take on more apprentices and—particularly where technology exposure is high—because these apprentices bring new skills.

Figure E2 splits the sample in treated firms that train in the updated occupations and treated firms that do not (including both non-training firms and firms training apprentices in occupations without an update). Investment increases are seen in both groups, but are larger in treated firms that do not only employ but also train workers in the updated occupations, indicating that the investment response is in part driven by firms that directly produce—and disproportionately benefit from—the new-skilled workers.

Together, these results document that curriculum updates trigger complementary capital investments, concentrated in technology-exposed occupations and in the firms that train workers in updated curricula. Capital-skill complementarity thus offers one mechanism amplifying the wage returns to new skills documented in Section 4.2: firms that invest in updated capital equipment raise the returns to the skills their new-trained workers bring.

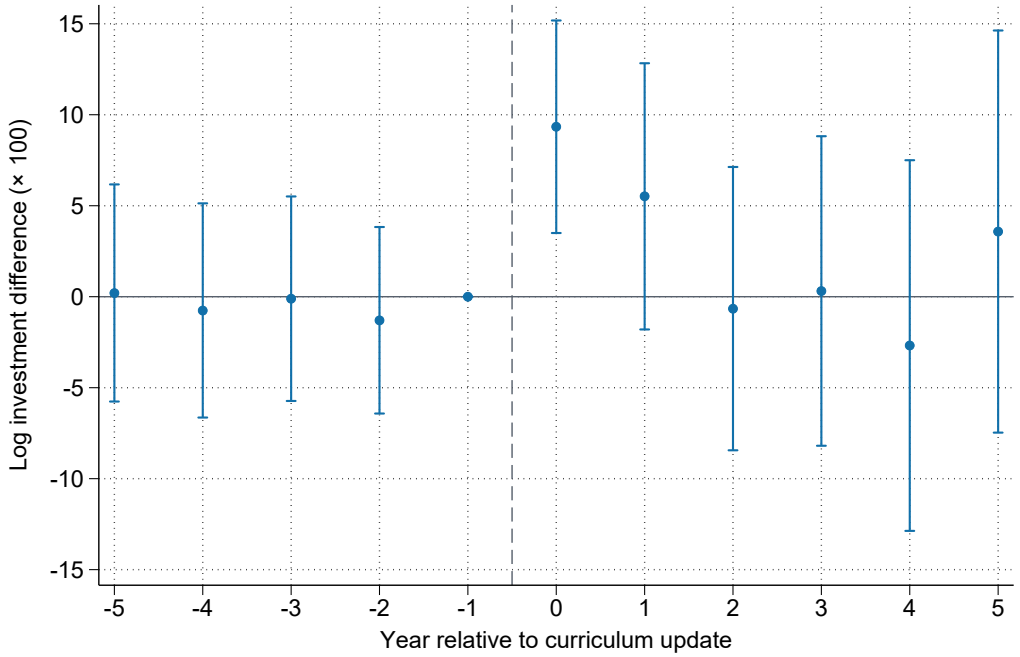
Table E1: Firm Investments: Descriptives of Stacked and Matched Firm Sample

	A. Treated			*B. Control*		
	Mean	SD	Median	Mean	SD	Median
Any investment (1/0)	0.74	0.44	1	0.74	0.44	1
Absolute investments in €1,000	3,148	19,475	60	1,716	6,049	50
Log(investments)	5.54	2.47	5.30	5.34	2.36	5.19
Number of workers	270	1,066	39	194	456	36
Manufacturing/service sector (1/0)	0.55	0.50	1	0.18	0.39	0
Share of workers with vocational training	0.76	0.19	0.79	0.72	0.23	0.76
Share of trainees	0.06	0.10	0.03	0.05	0.10	0.01
Share of workers in two main occupations	0.69	0.23	0.68	0.78	0.21	0.81
N unique firms		2,372			2,308	

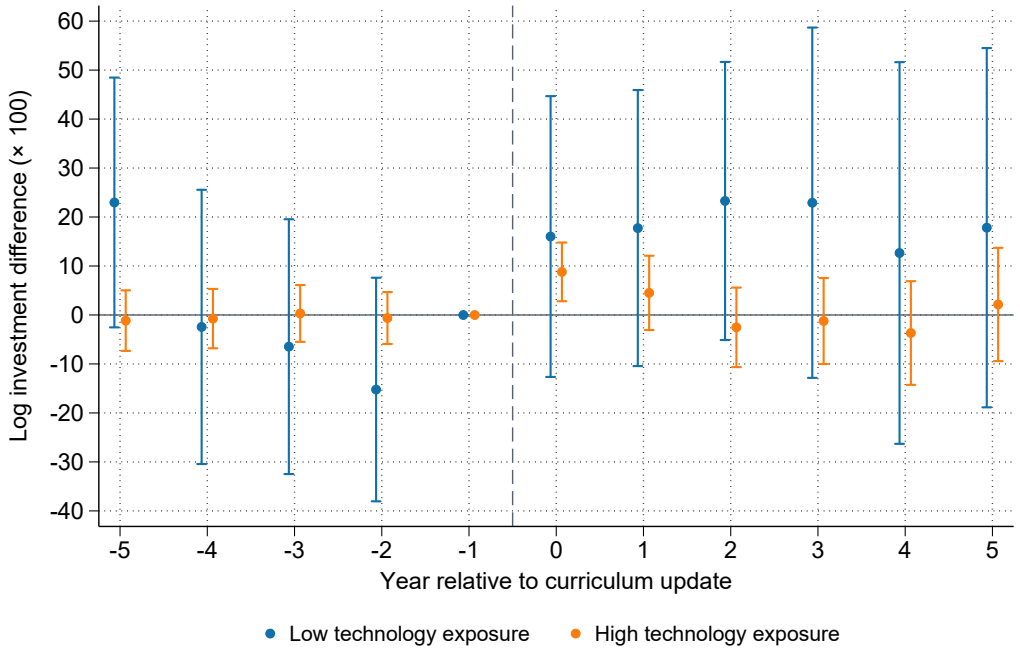
Source: LIAB. For years $\tau = -1$.

Figure E1: Investment Impacts of Curriculum Updates

A. Overall

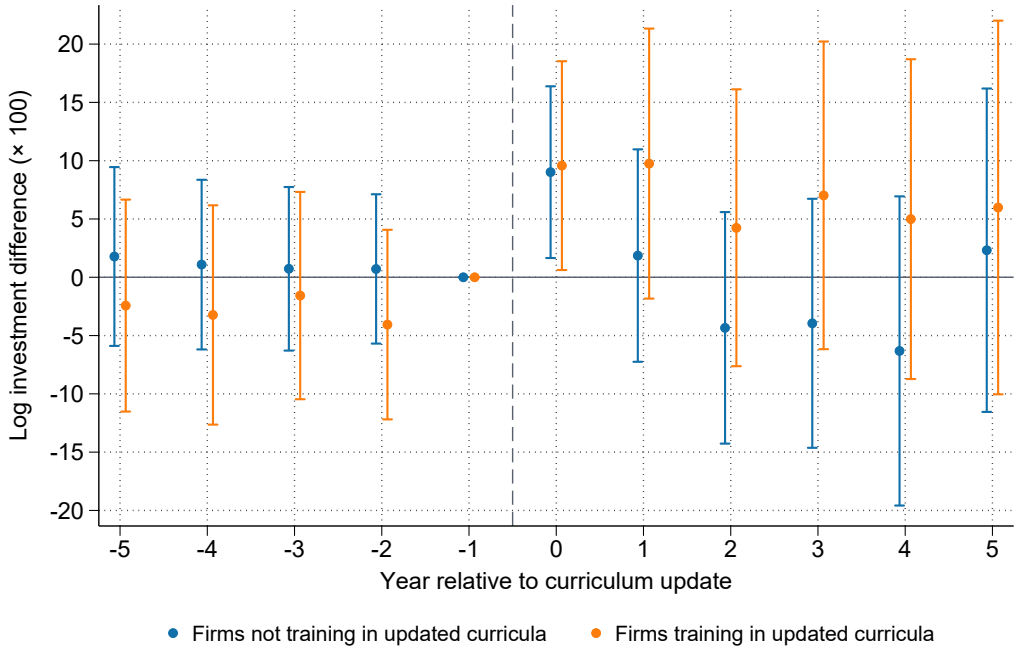


B. By Technology Exposure



Stacked difference-in-differences estimates of equation (**??**) using log investments as the dependent variable, and 95% confidence intervals. Panel A: $N = 70,850$ (151 events). Panel B: $N = 4,793$ for low exposure (24 events), and $N = 65,355$ for high exposure (123 events).

Figure E2: Investment Impacts of Curriculum Updates by Type of Training Firm



Stacked difference-in-differences estimates of equation (**??**) using log investments as the dependent variable, and 95% confidence intervals. 151 events. $N = 45,354$ for firms not training in updated curricula, and $N = 29,045$ for firms training in updated curricula.

F Curriculum updates and additional worker training

Our evidence of skill obsolescence for (older) occupational incumbents in Section 4.3 suggests that these workers do not receive sufficient additional training to keep their skills up to date. Nonetheless, curriculum updates for entrants could induce additional training efforts by firms for their existing workforce. Specifically, curriculum updates may generate additional training through two distinct mechanisms: a direct implementation margin in firms that train apprentices in the updated occupation (including the need to 'train the trainers'), and a broader workforce-adjustment margin in all firms employing incumbent workers in occupations where entrants are known to have updated skills.

As in Appendix E, we use LIAB data to examine these effects, retaining firms that are observed for at least three years. We limit the sample to 2003 onward, when firms are asked whether they provide training to their vocationally trained workers, during work hours and while covering the monetary costs fully or at least partly—that is, employer-paid training. These training measures can include external and internal courses or seminars, workplace-based training, lectures or conferences, job rotation, self-directed learning, quality or workshop circles, and other training activities.

As before, we designate firms as treated if the curriculum updates for at least one of their two largest occupations in terms of pre-update employment share. Treatment therefore captures firms that are highly exposed to vocationally trained labor in an updated occupation. We estimate a stacked-event DiD model at the firm level:

$$Y_{ft} = \sum_{\substack{\tau=-5 \\ \tau\neq-1}}^{5} \beta_\tau \text{Update}_f \times I_\tau + \delta_f + \gamma_\tau + \varepsilon_{ft} \ , \tag{F1}$$

where Y_{ft} is a binary indicator for whether firm f provides training measures for vocationally trained workers in year t. Event time τ is normalized such that $\tau = 0$ is the year trainees enter vocational training under a new curriculum. Update_f is the firm-level treatment indicator, while δ_f and γ_τ denote firm and event-year fixed effects. As before, all indices refer to the index by event. We cluster standard errors at the event-by-firm level.

$$Y_{fte} = \sum_{\substack{\tau=-5 \\ \tau\neq-1}}^{5} \beta_\tau \, \text{Update}_{fe} \times I_{\tau e} + \delta_{fe} + _{te} + \varepsilon_{fte} \ ,$$

where Y_{fte} is a binary indicator for whether firm f provides training measures for vocationally trained workers in calendar year t in event e. Event time τ is normalized such that $\tau = 0$ is the year trainees enter vocational training under a new curriculum. Update_{fe} is the firm-level treatment indicator, while δ_{fe} and λ_{te} denote firm and calendar year fixed effects, both interacted with event dummies. We cluster standard errors at the event-by-firm level.

Table F1 shows descriptive statistics for the treated and control samples. In the pre-

Table F1: Firm Training: Descriptives of Stacked Firm Sample

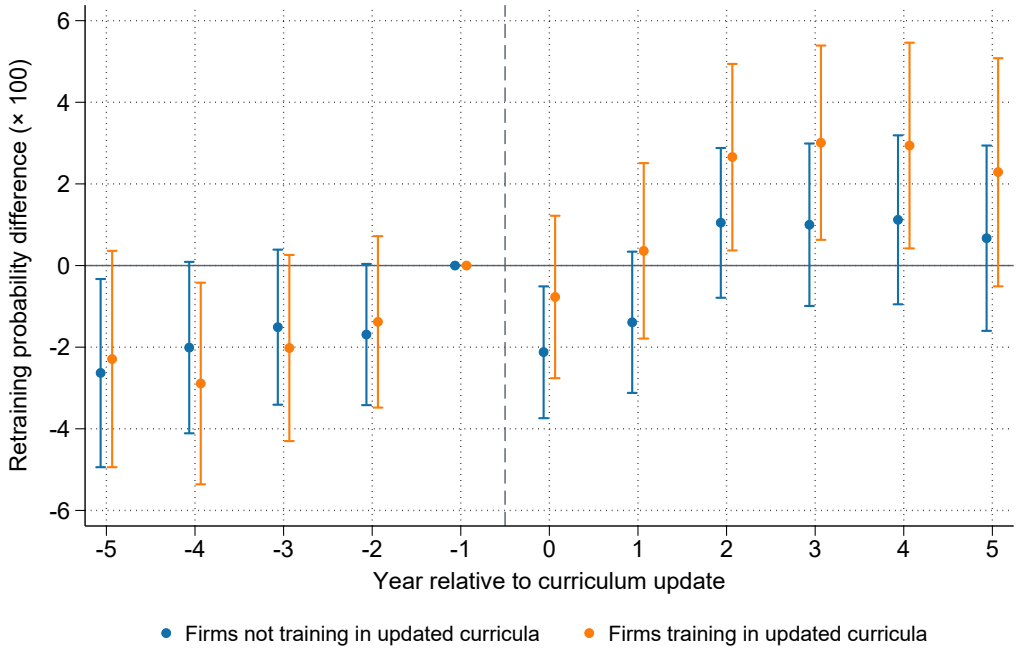
	A. Treated			*B. Control*		
	Mean	SD	Median	Mean	SD	Median
Training measures (1/0)	0.68	0.47	1	0.64	0.48	1
Number of workers	265	1,280	36	143	467	22
Manufacturing/service sector (1/0)	0.53	0.50	1	0.17	0.38	0
Share of workers with vocational training	0.76	0.20	0.79	0.71	0.27	0.76
Share of trainees	0.06	0.11	0.03	0.05	0.11	0.00
Share of workers in two main occupations	0.72	0.24	0.72	0.83	0.22	0.88
N unique firms		6,451			11,566	

Source: LIAB. For years $\tau = -1$.

treatment year, 68% of treated firms and 64% of control firms provide some training to vocationally trained workers.

Figure F1 shows that curriculum updates generate an increase in employer-paid training concentrated among firms that themselves train apprentices in the updated occupation. In these firms, the probability of providing training rises only modestly, by approximately 2–3 percentage points from two years after the update onward. Point estimates in the pre-period are somewhat negative, so this increase may partly reflect an upward trend, though the pre-period coefficients are individually imprecise. We find no corresponding increase among firms that intensively employ workers in the updated occupation but do not train apprentices in it. The response therefore appears to reflect the direct costs of implementing the new curriculum, rather than a broader effort to update the skills of incumbent workers. Together with the wage losses experienced by occupational incumbents when newly skilled entrants arrive, this limited response is consistent with employer-provided retraining being insufficient to prevent skill obsolescence among the existing workforce.

Figure F1: Training Impacts of Curriculum Updates by Type of Training Firm



Stacked difference-in-differences estimates of equation (F1) using a dummy for firm-level training measures as the dependent variable, and 95% confidence intervals. 237 events. $N = 2,323,416$ for firms not training in updated curricula, and $N = 2,306,355$ for firms training in updated curricula.