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Expertise at Work: 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 relevant expertise? We study how digital technology transforms skill acquisition and the resulting impacts on workers' careers. 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. Technological change spurs curriculum updates, and training content shifts toward digital and social skills while reducing routine-intensive task content, predominantly through new skill emergence. 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 curriculum updates enable workers to adapt to new skill demands: new-skilled workers earn higher wages, with wage increases of up to 5.5% for technology-exposed occupations. In contrast, the oldest occupational incumbents experience wage declines, indicating skill obsolescence. Firms increase capital investments when exposed to workers with updated skills, consistent with enhanced capital-skill complementarity. These findings highlight the central role of within-occupation skill supply adjustments 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 is among the most powerful forces shaping skill demands. Digital technologies raise demand for competencies such as IT and social skills (Deming, 2017; Cortes et al., 2021; Aghion et al., 2023), while reducing labor demand in routine tasks through automation (Autor et al., 2003; Acemoglu and Autor, 2011; Goos et al., 2014; Restrepo, 2024). The canonical race between education and technology emphasizes rising educational attainment as the primary mechanism through which skill supply adapts—a force that continues to shape wage inequality (Tinbergen, 1975; Goldin and Katz, 2008; Acemoglu and Autor, 2011). Yet technological change also transforms which skills matter, not only how much education workers need. While the literature on the skill demand side is extensive,[1] we know remarkably little about supply-side responses: whether educational systems adapt their content *within* programs or occupations to meet evolving skill demands, and whether such adaptation helps workers acquire relevant expertise. This asymmetry is striking given that within-occupation task changes—not just compositional shifts across occupations—account for the majority of aggregate changes in skill demand (Spitz-Oener, 2006; Atalay et al., 2020). Understanding whether and how skill supply adjusts within occupations through educational content adaptation is therefore essential to understanding how labor adapts to technological change.

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 administrative records over 1975–2018 and measures of technological progress, we answer three core questions. First, does advancing technology spur curriculum updates? Second, how does curriculum content evolve, and how do these within-occupational adjustments in skill supply compare to between-occupational shifts? Third, do skill updates affect workers' labor market outcomes, improving outcomes for new-skilled labor market entrants while inducing skill obsolescence among older occupational incumbents? Together, the answers to these questions address whether educational content adaptation can reinstate workers' expertise—their capability to perform economically valuable tasks (Autor and Thompson, 2025)— as technology advances.

[1] This literature considers how technologies such as computers, robotics, or AI reshape skill requirements by automating some tasks, complementing others, and creating new labor-using ones. Recent examples include Acemoglu and Restrepo (2019); Webb (2019); Acemoglu et al. (2020); Acemoglu and Restrepo (2022); Acemoglu et al. (2022); Hémous and Olsen (2022); Kogan et al. (2023); Autor et al. (2024); Bonfiglioli et al. (2024); Bessen et al. (2025); Hampole et al. (2025).

Vocational training in Germany is a full-time educational program following high school, and offers an ideal setting for studying these questions. First, the 1969 Vocational Training Act mandates that virtually all German vocational training is codified in nationally standardized, legally binding curricula that are regularly updated through an institutionalized process (discussed in detail in Section 2). This setting allows us to observe comprehensive, detailed educational content changes over half a century, and to know precisely which skill vintage individual workers were trained in—which is infeasible in most educational systems where curriculum decisions are uncodified or decentralized. Second, it covers occupational skill acquisition for a broad swath of the German labor market: vocationally trained workers constitute 70% of the German workforce over the period we consider (compared to 12% with a university degree).[2] Vocational training programs prepare workers for a wide range of jobs in both manufacturing and services, including administrative, logistics, and retail jobs and various technical occupations in automotive industries, in machine-building and -operating, and in electrical engineering. Third, 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). By studying these non-college educated workers' formal skill acquisition, we examine adaptation mechanisms where they matter most: in occupations where automation has fundamentally reshaped skill demands.

We employ two main empirical strategies to answer our research questions. First, to identify the effect of technological change on curriculum updates and content, we link vocational training curricula to lagged patents using Natural Language Processing (NLP) techniques, following a method pioneered by Seegmiller et al. (2023). To establish a causal connection, we use breakthrough technologies (Kelly et al., 2021), which reflect discontinuous changes in the innovation space that are plausibly exogenous to subsequent changes in skill supply. We also use NLP techniques to analyze and classify skill content embodied in curriculum updates. Second, to identify the causal effect of curriculum updates on individual worker outcomes, we use a stacked difference-in-differences (DiD) model that leverages 365 curriculum update events. Our DiD compares worker cohorts with old skills and worker cohorts with new skills in occupations that experience curriculum changes to corresponding cohorts in occupations without curriculum changes over the same time window. This identification strategy rests on the discontinuity of the skill supply change. Potentially confounding fac-

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

tors such as changing skill demand plausibly evolve more smoothly over time, and we also show models controlling for each curriculum's underlying technology exposure. We also estimate DiD models (using curriculum updates, as before) to study skill obsolescence among occupational incumbents, and capital investment responses among firms.

We establish four sets of findings. First, technological advances spur curriculum updates: occupations more exposed to digital technology update their training content more frequently and more rapidly. A standard deviation increase in technology exposure raises the annual curriculum update probability by 1.24 percentage points—a 33% increase relative to the 3.8% average annual probability of curriculum updates.

Second, curriculum updates have brought about substantial shifts in training content over the past five decades. Digital and social skills have increased while routine task intensity has strongly declined—especially among technology-exposed occupations— predominantly through new skill emergence rather than skill removal. This indicates workers acquire new expertise in tasks complementary to advancing technology. This adjustment margin is quantitatively important: within-occupation skill adjustments account for two-thirds of aggregate vocational skill supply changes in routine task content.

Third, curriculum updates generate sizable wage returns for new-skilled workers. Using administrative employer-employee data, we show that labor market entrants trained under updated curricula on average earn 3.3% higher wages than those trained under outdated curricula in the same occupation, relative to occupations without curriculum updates. Returns reach 5.5% for technology-intensive curriculum updates, and reflect absolute improvements—faster wage growth for new-skilled cohorts, not deterioration for controls. Workers with updated skills also stay in their trained occupations at higher rates, and move to higher-paying firms. These effects are not driven by changes in trainee composition, and remain when controlling for the prior curriculum's technology exposure.

Our final set of results considers the consequences of new skill supply for the value of pre-update skills and firm capital investments. Skill updates have heterogeneous effects on incumbent workers. The oldest incumbent workers (ages 55–65) experience wage declines of up to 9.7% when new-skilled workers enter their occupation (partly by moving to lower-paying firms), consistent with skill obsolescence. Younger incumbents do not experience wage declines but respond by switching occupations more frequently. We also show that firms exposed to workers trained in updated curricula increase capital investments, especially for technology-intensive curriculum updates, in line with enhanced capital-skill complementarity for workers with new skills.

Our study contributes to several economic 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). A key insight of this literature is that technological advances change the skills demanded in the labor market, both by displacing labor from existing tasks through automation and by complementing labor in existing tasks and creating new labor-using ones. We contribute to this literature by providing the first systematic and long-run evidence of how skill supply adapts to technological advances through educational content—not just educational attainment. We demonstrate that these within-occupation skill supply adjustments help reinstate the relevance of workers' expertise: they are quantitatively important, predominantly driven by the addition of new skills, and causally linked to improved worker outcomes for those with updated skills.

Second, we contribute to a literature studying within-occupational task change. This literature documents the importance of within-occupation task changes in accounting for aggregate changes in skill demands (Spitz-Oener, 2006; Atack et al., 2019) including new task emergence within occupations (Lin, 2011; Autor et al., 2024), and has developed multidimensional measures of occupation-level human capital using job vacancies and task descriptions (Atalay et al., 2020; Deming and Noray, 2020; Acemoglu et al., 2022; Deming, 2023). Distinct from this demand-side approach, we develop multidimensional measures of human capital on the labor supply side, and establish technological change as a driver of within-occupational skill supply adjustments. Our analysis also illuminates the supply-side mechanisms that enable workers to acquire expertise for the new occupational tasks emerging on the demand side. Mirroring the literature's finding that within-occupation task changes account for the majority of aggregate task demand shifts, we show within-occupation skill adjustments account for the majority of aggregate supply changes.

Third, our work relates to a literature on skill obsolescence in the context of technological change (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 within this literature is Janssen and Mohrenweiser (2018), who pioneer a case study of a German vocational curriculum update for a single occupation in response to Computerized Numerically Controlled (CNC) machinery adoption. They show that this curriculum update deteriorated labor market outcomes for incumbent workers in the occupation, indicating skill obsolescence. We contribute by analyzing curriculum changes for the near-universe of vocational training occupations in Germany over the past five decades and all (patented) technology these occupations are exposed to, and by identifying the causal effect of technological change on educational content. Relative to the broader skill obsolescence literature, we make two additional contributions. First, we identify several hundred specific educational updates and their skill content allowing us to directly observe obsolescence-causing events, and second, beyond studying skill obsolescence among (occupational) incumbents, we identify the gains to workers with updated skills. The emergence of new valuable expertise does not necessarily follow from skill obsolescence. Just as task displacement can occur without new task creation, incumbent workers' skills may become obsolete without corresponding benefits to new cohorts of workers, for example if workers' previous expertise is now embodied in technology and therefore no longer scarce.

Fourth, we contribute to an emerging literature on educational content change. Recent work examines how educational programs respond to shifting labor and student demand (Conzelmann et al., 2023; Light, 2024) and how demand for college programs responds to regional robot exposure (Di Giacomo and Lerch, 2023). Within higher education, Boustan et al. (2022) document that universities introduce more CNC-related degree programs following the adoption of this technology, while Biasi and Ma (2023) show that larger gaps between university curricula and the academic knowledge frontier are associated with worse student outcomes. At earlier stages of education, Hermo et al. (2022) document a shift in Swedish primary school curricula from factual knowledge toward reasoning skills. A related broader literature analyzes the content of European vocational curricula by cataloging curriculum skills and their relationship with wages (Eggenberger et al., 2017, 2018; Rupietta and Backes-Gellner, 2019; Kiener et al., 2022, 2023; Langer and Wiederhold, 2023; Schultheiss and Backes-Gellner, 2024; Buehler et al., 2025; 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 on worker outcomes — enabled by our comprehensive 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 in Section 4.2 and occupational incumbents in Section 4.3), and studies impacts on firm investments (Section 4.4). 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 Training occupations and training 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 apprenticeships 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. 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. 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]

[3] Vocational training at vocational schools only, including training in health, education and 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] Curricula for the part of the dual training taught in vocational schools are developed in close coordination with the on-the-job training curricula that we study, and therefore arguably feature closely corresponding changes (Kultusministerkonferenz, 2021).

[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

While this institutional setting uniquely allows us to observe curriculum content and its updates comprehensively over 50 years (as well 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 C 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 training 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 curricu-

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.

[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.

lum 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 title 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 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 mar-

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

ket, Figure 1 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. While daily wages in training occupations vary meaningfully, with an interquartile range of 83 to 110 euros; the interquartile range for other jobs is significantly wider, at 94 to 172 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 in Germany is below 40% (2018), lower than some other European countries like France or Italy, where it is closer to universal (Jäger et al., 2025).

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, Figures 2 through 5 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.

Figure 2 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 3 shows excerpts illustrating changes in the 2003

[13] Appendix Figure A1 presents the wage distributions of vocationally trained workers and for all other workers, showing the same pattern.

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 (Figure 5) relative to its 1978 version (Figure 4). 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 6 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 7 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, curricula are updated after 15.3 years, as seen from the bottom row of Panel A in Table 2. The distribution of curriculum change intervals varies substantially across broad occupation groups, shown in panel B of Figure 7: the curricula for IT and scientific service occupations (comprising 5.7% of all curricula) are updated with the highest regularity, followed by Business service occupations (comprising 8.8% of all curricula), Production occupations (comprising 64.6% of all curricula), and Other commercial service occupations (comprising 12% of all curricula). Personal service occupations (comprising 9.0% of all curricula) receive the least frequent updates on average, though 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.

Rather than using all U.S. utility patents, we focus on the subset 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 (following Autor

[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.

et al. (2024) who use the same lag length for measuring exposure of occupational content 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 workers. 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 strategy and provide supporting evidence). Lagging breakthroughs by twenty years also allows for a delay between patenting these novel technologies and subsequent follow-on innovation as well as implementation in the workplace. 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 8 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] 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

[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 B1 shows the number of tokens contained in curriculum texts used for matching to patent texts—the average curriculum has 34,374 tokens.

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 B2 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, and sum them for each curriculum: the resulting occupational patent count is 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 9. 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 A2 highlights that overall and digital technology exposure are strongly positively correlated in both halves of our 50-year period. Examples of highly exposed jobs for both digital and overall technology are Electrical machine builders, Mechanical engineering mechanics, and Body and vehicle builders. Least exposed on both dimensions are Funeral workers, Housekeepers, Clothes tailors, and Barbers. However, there are some differences, with for example Industrial clerks, Photographers, and Film and video editors more exposed to digital than overall technology; and the reverse being true for Glassmakers, Distillers, and Orthopedic technology mechanics.

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 B4 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.

3 Does technology exposure spur curriculum change?

This section examines whether technology exposure spurs curriculum change. We first analyze whether occupations 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

Overall update probability. Figure 10 presents a Kaplan and Meier (1958) survival plot of curricula that update during our observation window, 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:

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

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 address 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 0.44–0.51 percentage points in the unweighted models, and 0.79–0.84 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 B3, 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 (0.49×2.58, 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 2.14 percentage points (0.82×2.61, column 4), a 42% increase relative to the weighted baseline of 5.1%.[18]

[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.

Intensive margin: speed of updates. We complement the annual panel analysis with a cross-sectional approach examining the duration until curricula are updated. Using each curriculum's first observation, we estimate:

$$\text{Years until update}_{kj(\tau)}|\{\mathbb{1}(\text{Update})_{kj}=1\}=\beta\text{Tech}_{kj,[\tau-25;\tau-20]}+\theta_{kj,\tau}+\zeta_J+\delta\frac{E_{jt_0}}{E_{t_0}}+\varepsilon_{kj(\tau)} \quad (2)$$

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.[19] 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 6 shows that technology-exposed occupations update more rapidly. Doubling technology exposure accelerates updates by approximately 8 months ($= -0.63 \times 12$ 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.

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 11% of curriculum text (see Appendix Table B1). Nonetheless, curricula with exam content more exposed to digital technology update more frequently (Appendix Table B7) and more rapidly (Appendix Table B8). Second, Appendix Table B9 demonstrates that our results

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

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 patents held by German inventors.

Types of curriculum updates. Table 7 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.[20] 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. Appendix Table B10 shows similar results when weighting models by occupational employment shares.

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:

$$\mathbb{1}(\text{Update})_{kj[t+T]} = \beta \text{Tech}_{k,[t-5;t]} + \eta \text{Tech}_{kj,[t-5;t-10]} + \gamma_t + \theta_{kj,\tau} + \delta \frac{E_{jt_0}}{E_{t0}} + \zeta_{J\times t} + \varepsilon_{kjt} \quad (3)$$

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 11 plots the estimated β coefficients for separate regressions with increasing T (blue series). Technology exposure has a minimal immediate effect on curriculum updates:

[20]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.

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 exposure.

3.2 Changes in curriculum content

Having established that technology exposure drives curriculum updates, we now examine how training content evolves. We expect curricula to evolve towards tasks and skills complementary to digital technology, specifically, increased use of digital technologies and social skills, reduced routine task content, and greater task complexity. 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 Skill content change

We estimate descriptive models to study changes in skill content:

$$\text{skill}_{kjt}|\{\mathbb{1}(\text{Update})_{kj}\} = \beta t + \delta_j + \varepsilon_{kjt} \ , \tag{4}$$

where skill_{kjt} is a skill measure of curriculum k for training occupation j in year t. The coefficient β on the linear time trend captures the average annual change in skill content (in standard deviations) across curricula. Since content changes occur by definition at the intensive margin, we estimate equation (4) 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,[21] 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 (4) separately for training occupations with above-median versus at or below-median technology exposure, measured in the year each curriculum was first observed to avoid including endogenous changes in curriculum content. We expect β to

[21] This results from the growing number of curricula, see panel B of Figure 6.

be positive, and larger for highly technology-exposed occupations.

Digital technology and social skills. We first 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 Appendix Table B5. We estimate equation (4) with the occurrence of these digital or social keywords as the dependent variable, among updated curricula.

Figure 12 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 0.05 percentage points cumulatively over the entire period ($0.012/1{,}000 \times 100$ percentage points annually $\times$ $(2021-1976)$). This pattern is more pronounced for highly technology-exposed curricula, which experience a cumulative increase of 0.10 percentage points ($0.023/1000 \times 100$ $\times$ $(2021-1976)$). 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 12 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.[22]

Routine task content. We next study how curriculum updates affect routine task content, 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 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.[23] 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.

We define routine task intensity as the sum of a curriculum's cosine similarities to the two routine tasks, minus the sum of its similarities to the three non-routine tasks. Routine task intensity (RTI) for training curriculum k is therefore:

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

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

[22] Appendix Figure A4 highlights that these patterns exist both in production and service occupations, though are more pronounced in the former. Appendix Figure A5 shows qualitatively similar results when not conditioning on curriculum change.

[23] 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 B11 lists specific O*NET items used for each of the five task groups.

Appendix Table B12 shows the most and least routine intensive curricula cross-sectionally. Among the most routine intensive are curricula for Embroiderers, Confectioners, Glassmakers, Dressmakers, Clothes tailors, Bakers, and Basket makers. By contrast, among the least routine intensive curricula are those for Sports specialists, Personnel services clerks, Marketing communication clerks, Market and social research specialists, and Event managers.[24] These occupational routine task intensity rankings are consistent with the literature, giving us confidence that our methodology accurately captures curricula's routine task content.

We examine how curricula's routine task intensity evolves over time by estimating (4), with standardized curriculum RTI (zero mean, unit standard deviation).

Figure 13 plots estimates of β (and 95% confidence intervals), showing a clear downward trend in curricula's routine task intensity. Annually, RTI decreases 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 declines 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 less routine-intensive tasks, especially in occupations highly exposed to digital technologies.

Figure 13 reveals that these trends hold in both production and service occupations, even though the decline is somewhat more pronounced among production occupations, which constitute two thirds of training curricula. However, the decline in routine intensity 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).[25,26,27]

Table 8 uses representative SIAB data to document that these within-occupation skill

[24] Appendix Table B13 shows the most and least routine intensive curricula separately for each of the five broad occupation groups. Appendix Figure A3 shows that routine task intensity is negatively correlated with occupational employment growth, as expected.

[25] Appendix Figure A6 shows qualitatively similar results when not conditioning on curriculum change, except that the differential decline in routine task intensity for technology-exposed occupations is driven by production jobs only.

[26] 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 routine task intensity.

[27] Appendix Figure A7 shows that curricula are also becoming more complex, measured by the share of curriculum words outside a typical eighth-grader's vocabulary (Dale and Chall, 1948). 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 ($r = -0.63$).

adjustments through curriculum updates account for two-thirds of the aggregate decline in routine task content of vocational occupational skill supply. We compute the number of vocational trainees with reasonable training durations in West Germany per occupation and year, and assign each trainee their training occupation's curriculum-based routine task intensity. We decompose the total change in 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.[28] The routine task content of vocational skill supply decreased by 0.95 standard deviations over these 45 years, with 0.63 standard deviations (66.0%) stemming from the within-occupation component, and the remainder reflecting the changing occupational composition of trainees. 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.

3.2.2 New skill emergence and skill removal

The changes in vocational skill content may arise from new skills being added when curricula are updated ('new skill emergence'), continuously existing skills receiving a different weight in the new curriculum compared to the old one ('intensive margin skill changes'), or skills being removed ('skill removal'), or some combination thereof.[29] 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.[30]

[28] We compute $\Delta \mathrm{RTI}_{1976,2021} = \sum_j \Delta \mathrm{RTI}_{j,1976,2021}(w_{j,1976} + w_{j,2021})/2 + \sum_j \Delta w_{j,1976,2021}(\mathrm{RTI}_{j,1976} + \mathrm{RTI}_{j,2021})/2$, with w_j occupation's j trainee employment share in the respective year. For years before we observe an occupation's first curriculum, we use the routine task intensity of the occupation's first observed curriculum. This arguably yields a conservative estimate of the within-occupation component.

[29] Buehler et al. (2025) study curriculum design by considering removed and added word shares in Swiss curricula.

[30] 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. 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.

Appendix Figure A8 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).[31]

Importantly, intensive margin skill changes, skill removal, and new skill emergence play distinct roles in changing curriculum skill content. Figure 14 illustrates this for changes in non-routine task intensity by plotting 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 had the same non-routine task intensity as the previous curriculum's remaining words, leaving overall routine task intensity unchanged. Observations above (below) the line are higher (lower) in non-routine task intensity than the previous curriculum, shifting it to become less (more) routine-intensive. Panel B shows analogous patterns for curriculum word complexity, measured as the share of complex words.

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.[32] 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 change along the intensive margin, represented by changing frequency of remaining words, and skill removal also contribute, though to a lesser extent. Intensive margin skill change tends to increase non-routine task intensity, especially for curricula that are already relatively non-routine intensive; and is mostly neutral for curriculum complexity. Skill removal has a heterogeneous effect on non-routine task intensity. Words removed from the most routine curricula are more routine— thereby increasing an updated curriculum's non-routine task content. However, words removed from most non-routine curricula are more non-routine, increasing an updated curriculum's routine intensity slightly.

[31] Appendix Figure A9 shows that word removal and addition are not strongly correlated across curriculum updates, but do vary substantially.

[32] Appendix Figure A10 show analogous results for task complexity, with similar findings.

The results in Figure 14 demonstrate that curriculum content change arises from 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 erodes it for occupational incumbents trained in the previous curriculum.

4 The labor market impacts of curriculum updates

The preceding analysis establishes that technological advances spur updates in vocational training curricula, driving training content to evolve towards skills more complementary to digital technology, predominantly through new skill emergence. We now ask: do these updated skill sets improve workers' post-training labor market outcomes? If curriculum changes enable workers to meet evolving skill demands, workers trained with updated curricula should fare better in the labor market than those trained in outdated ones. Conversely, occupational incumbents should experience skill obsolescence when workers with updated skills enter their occupation. We examine both predictions here, along with consequences for firm's capital investments.

4.1 Sample construction

We use SIEED data (Berge et al., 2020) as our primary employer-employee dataset.[33] 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. 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.

We observe workers' apprenticeship training spells, which indicate when workers start and complete their training program and which occupation they train in. Combined with our curriculum dataset, this allows us to determine which curriculum vintage each worker is trained in. We restrict our sample to workers whose training curriculum we observe,

[33]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.

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. Appendix D provides further details on data construction.

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 analyze both labor market entrants (Section 4.2) and occupational incumbents (Section 4.3) below.

For occupational employment descriptives (including when using these as control variables) discussed in Section 2.1, we use SIAB data (Graf et al., 2023).[34] 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?

4.2.1 Empirical approach

To identify the causal impact of curriculum updates on post-training worker outcomes, we employ a difference-in-differences event study design comparing outcomes for cohorts of workers with old skills (‘old-skilled workers’) and cohorts of workers with new skills (‘new-skilled workers’) in occupations with training updates against worker outcomes in occupations where no such update occurred around the same time. We focus on labor market entrants, who we define as vocationally trained workers in the first 5 years after completing their training.

[34] 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.

We estimate

$$Y_{ijt} = \sum_{c=[-5,5]} \beta_c \text{Update}_j \times I_c + \sum_{c=[-5,5]} \alpha_c I_c + \delta_j + \gamma_t + \mu X_{it} + \varepsilon_{ijt} \ , \tag{5}$$

where Y_{ijt} is an individual-level outcome for worker i who has been trained in occupation j in year t.

Update_j is a treatment dummy indicating whether occupation j experiences an update to its training curriculum during our time window: this separates our treatment group (workers trained in occupations with curriculum changes) from our control group (workers trained in occupations without curriculum changes in a window of 5 years before and 5 years after the treatment occupation's update).[35] c denotes cohorts of workers defined by the start year of their vocational training relative to the year of the curriculum change. We normalize $c = 0$ to represent the first cohort trained in the new curriculum: 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 focus on worker cohorts whose training started in a window of 5 years before and 5 years after the treatment occupation's update, i.e. $c = [-5, 5]$.

Treatment is staggered because different curricula update in different years, so we cannot use the two-way fixed effect estimator (de Chaisemartin and D'Haultfoeuille, 2020; Sun and Abraham, 2021; Goodman-Bacon, 2021; Callaway and Sant'Anna, 2020). Instead, we stack observations for different events (i.e. different curriculum updates) following Cengiz et al. (2019).[36] This stacking implies that workers and occupations can occur multiple times in the data as controls; and occupations can also occur multiple times as treated, if their training curriculum updates more than once. Therefore i indexes individual workers by curriculum update ('event'), j indexes occupations by event, and t indexes calendar years 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 365 curriculum update events, with 226,077 unique treated workers and

[35] 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.

[36] 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 (2020) 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 (2021); Bessen et al. (2025).

257,779 unique control workers. Control group workers are weighted by $1/n_i$, with n_i the number of controls for treated worker i.

This approach uses repeated cross-sections of worker cohorts rather than a worker panel, since pre-training (i.e. pre-treatment) labor market outcomes do not exist. The first difference in our difference-in-differences strategy is the difference in outcomes between 'old-skilled' cohorts (workers trained in the old curriculum) and 'new-skilled' cohorts (workers trained in the new curriculum) within the same occupation. The second difference is the difference in outcomes between treated workers (trained in occupations that updated) and control workers (trained in occupations that did not update over the same time window).

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.

We control for calendar year (γ_t) and training occupation (δ_j) dummies as well as worker characteristics (X_{it})—age, and gender. We interact all control variables with event dummies as is standard in stacked designs. We cluster standard errors at the level of treatment: occupation by event.

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 anticipatory reactions by firms, and (iii) SUTVA. We provide empirical support for these assumptions in several ways. First, we show there are no significant pre-trends in worker outcomes. Second, 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 need not reflect returns to new skills. In Appendix E, we therefore extensively examine changes in trainee composition, finding no evidence of changes around curriculum updates, consistent with parallel trends and no anticipation. Third, we show that positive wage effects are driven by faster wage growth for treated cohorts, not deterioration for control group cohort—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, in Section 4.3 we directly study the impact of an influx of new-skilled workers on *young* incumbent workers, finding no evidence of significant wage impacts, indicating that the pre-treatment entrant cohorts are also unlikely to have been directly affected, consistent with SUTVA.

We consider the role of technology by studying outcomes separately for high- and low-technology exposed occupations; by estimating event-level models and correlating outcomes with technology exposure; and by controlling for the preceding curriculum's technology exposure.

4.2.2 Wage impacts

Table 9 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 70 euros, with a standard deviation of 30 euros. Most workers are employed year-round: the average number of annual working days is 268, with a median of 365. Workers are employed in relatively large firms (560 workers on average), though the median firm size is 40 workers. Appendix Table B14 shows corresponding descriptives for the stacked sample, separately for the $\tau = -1$ cohorts of treated and control group workers.

Panel A of Figure 15 presents estimates of equation (5), using log daily wages as the dependent variable with β_c coefficients multiplied by 100 for legibility. There is no evidence of pre-trends, consistent with treated and control group worker cohorts following similar wage trajectories before curriculum reforms. We find significant positive wage effects from curriculum updates, measured over workers' first five years after graduation from vocational training. These effects reach 3.3% higher daily wages for graduates of the new curriculum compared to graduates from the old curriculum— relative to a control group of graduates in occupations with no curriculum update. This is striking since we compare workers trained for the same occupation, but with an updated curriculum.

Positive wage effects emerge starting from cohort 2 onward, which is the third one trained in the new curriculum. Grace periods in implementing new curricula, discussed above, may contribute to the delay. This is particularly plausible since impactful and technology-driven curriculum changes, for which we observe larger wage returns (as documented below), more often receive grace periods. Incomplete compliance in immediately teaching the new curriculum could be another factor, though we cannot observe this.

Panel B shows similar patterns 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 workers. In further analyses of these labor market entrants, we therefore focus on the daily wage margin.

The positive wage returns highlight that educational content is racing to keep up with changing skill demands, and that graduates with updated skills earn a significant wage premium. Appendix Figure A11 shows predicted log wages for treated and control group workers, demonstrating that wage returns result from more rapid wage growth for treated worker cohorts after the curriculum update, not slower wage growth for control group workers. The wage premium for obtaining new skills thus reflects an absolute improvement, not just a relative one.

In Appendix E, we use a training occupation dataset 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 are not driven by improvements in trainee characteristics following curriculum updates. We also find no changes in exam pass rates or in program selectivity around curriculum updates, as proxied by the share of unfilled apprenticeship positions or unsuccessful apprenticeship applications. Further, Appendix Figure A12 shows that curriculum updates do not change the composition of training firms (for example because only higher-paying firms can effectively provide updated skills): training firm AKM (Abowd et al., 1999) fixed effects are unaffected by curriculum updates. This means that wage returns are not driven by workers having been trained in higher-paying firms and remaining there after training completion.

4.2.3 Mechanisms

Effects by technology exposure. To understand the mechanisms underlying improved wage outcomes for workers with updated skills, we first examine how wage impacts vary with updated occupations' pre-update technology exposure. While curriculum updates may occur for various reasons, technology exposure is an important driver, as Section 3.1 documents. Curricula updated in response to technological advances should generate larger wage returns if these changes align with evolving skill demands or induce complementary capital investments (as we study below).

Figure 16 reports wage returns to curriculum updates separately by 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 wage returns for new-skilled worker cohorts, and these wage premia are higher than for less technology-exposed occupations, especially for later cohorts. While no difference is visible for the first 'new-skilled' cohorts, cohorts trained in highly technology-exposed occupations three to five years after the curriculum update earn 2.8% (cohort 3), 4.1% (cohort 4), and 5.2% (cohort 5) higher wages over the first five years of their careers than the last cohort trained in the old curriculum ($c = -1$). Corresponding estimates for workers trained in low technology-exposed occupations stabilize at around 2.2%. Appendix Figure A13 shows these daily wage effects translate to higher annual earnings, with the largest 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 pure skill-supply effects. We address this concern by controlling for occupations' contemporaneous technology exposure based on the old curriculum, which reflects technology-driven demand changes had skill supply remained constant. Appendix Figure A14 shows that our results are unaffected.

To further assess the relationship between technology exposure and wage returns from skill updates, we estimate models separately by update event, and correlate the resulting update-specific wage returns with each curriculum's pre-update technology exposure. Figure 17 shows binscatters for these estimates over the range of technology exposure, separately for production and service occupations. Technology exposure is measured as the log of linked digital patent counts — Appendix Figure A15 shows corresponding binscatters when using the level of patent counts, i.e. including curricula with zero linked patents. Event-specific estimates are weighted by worker cohort size before constructing equally-sized bins. Low-exposure bins include Orthopedic shoemaker, Bicycle mechanic, and Stone mason and stone sculptor for production; and Barber and Tourism and leisure clerk for services. Medium-exposed bins include Hydraulic engineer, Carpenter, and Technical assembler for production; and Warehouse logistic specialist, Marketing communications clerk, and Medical assistant for services. The most-exposed bins include Systems IT specialist, Automobile mechanic, and Aircraft electronics technician for production; and Pharmacist and Media designer digital and print for services. Both figures reveal a positive relationship between a curriculum's pre-update technology exposure and the resulting wage return. This relationship holds within production and within service occupations, though wage returns are typically higher for production occupations overall.

This evidence suggests that skill updates spurred by advancing technology impart larger and longer-lasting labor market advantages than updates driven by other factors.

Worker mobility. To examine whether these labor market advantages accrue from differences in workers' early career paths, we use occupation, industry, and firm mobility as outcomes in equation (5).

Figure 18 displays mobility estimates relative to the worker's apprenticeship position: that is, we consider whether the worker has moved out of the 4-digit occupation, the 3-digit industry, or the firm where they did their apprenticeship. (Results are similar when considering year-on-year mobility, i.e. relative to the occupation, industry, and firm of the past year.)

A consistent pattern emerges: curriculum updates have no measurable impact on industry or firm switching, but reduce the probability of leaving the training occupation. This decrease in occupational mobility aligns with the timing of wage returns, becoming stronger for later cohorts. New-skilled cohorts are up to 2.9 percentage points less likely to move out of their training occupations over the first five years of their career. This is a moderately-sized effect compared to the baseline probability of occupation mobility of 34%, shown in Table 9.

Although new-skilled workers do not have differential rates of firm mobility, as shown in panel of A of Figure 18, the direction of mobility may still differ. Panel B therefore considers the average AKM fixed effect of the firms workers are employed in. We find some evidence that curriculum updates allow workers to move to higher-paying firms, especially for the latest cohort: workers' firm AKM fixed effect increases for the very last new-skilled cohort, by 0.03 standard deviations. (For high-exposure events, this increases to 0.05 standard deviations.)

Robustness checks. To understand how wage effects of curriculum updates evolve over the first five years of workers' careers, we estimate the model separately by workers' potential work experience. Appendix Figure A16 plots the estimates. 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. Comparing subplots reveals that wage returns grow relatively consistently over the first five years of the career. An additional benefit of these experience-specific estimates is that our baseline specification could contain spillover effects because we average wages over the first five post-training years. In that specification, old-skilled cohorts trained before the curriculum update partly earn their wages during years when new-skilled cohorts have already entered the labor market, potentially impacting the estimates for $c < 0$. The estimates shown in Figure A16 are therefore better identified under spillover effects.

We perform several additional robustness checks. First, Appendix Figure A17 shows that our results hold when we control for firm fixed effects, whether defined by the firm where workers completed their apprenticeship training or where they are employed. Effect sizes are reduced by approximately two-thirds when adding the latter firm effects, confirming that moves to higher-paying firms are part of the underlying mechanism. Second, Appendix Figure A18 shows that results are robust to excluding from the control group those occupations with the highest worker mobility to or from the treated occupations, or those within the same two-digit occupation: while estimates become somewhat less precise, the effect sizes are very similar. This mitigates concerns about SUTVA violations. Third, Appendix Figure A19 shows that wage effects are not driven by subsequent educational upgrading by new-skilled workers: 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.[37]

Skill updates thus provide labor market entrants with advantages through higher wages, coupled with increased occupational retention. These benefits concentrate in skill updates related to technological exposure, suggesting that changes in within-occupational skill supply play an important role in maintaining workers' expertise amid changing skill demands.

4.3 Do curriculum updates lead to skill obsolescence for incumbent workers?

Having established that new-skilled workers benefit from curriculum updates, we now study labor market outcomes of incumbent workers following curriculum updates. Curriculum updates bring an inflow of new-skilled workers into incumbents' occupations. We interpret declining incumbent wages as evidence of skill obsolescence.

Empirical approach. We construct a worker-level panel of vocationally trained workers, restricting the sample to occupational incumbents, defined as workers employed full-time in the same occupation for at least five consecutive years before that occupation received a curriculum update. We exclude apprentices and other workers not subject to social security

[37] 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.

contributions.

We exploit the fact that we can follow individual incumbents over time by analyzing changes in their labor market outcomes before and after curriculum updates. We estimate

$$Y_{ijt} = \sum_{t=[-5,5]} \beta_t \text{Update}_j \times I_t + \delta_i + \gamma_t + \varepsilon_{ijt}, \tag{6}$$

where t is normalized such that $t = 0$ is the year of the curriculum update. Y_{ijt} is an outcome for worker i employed in occupation j in year $t = [-5; -5]$. δ_i captures individual fixed effects, and γ_t relative time period fixed effects. We stack observations for different events, interact all controls with event dummies, and cluster standard errors at the level of treatment (occupation by event).

For each event, Update_j is a treatment dummy indicating whether occupation j has experienced a curriculum update, and therefore an inflow of workers trained in a new curriculum. This separates our treatment group (incumbents in occupations with curriculum updates) from our control group (incumbents in occupations without curriculum updates). All treated workers are exposed to curriculum updates in their employment occupation in $t \geq 0$.

The parameters of interest are β_t, which estimate the effect of exposure to entrants with new skills on a range of incumbent worker outcomes: log daily wages, log annual earnings, annual days in non-employment, and job mobility. For log wages, for example, we expect negative post-treatment estimates ($\beta_{t\geq 0} < 0$) if competition from new-skilled workers reduces the returns to incumbents' skills, indicating skill obsolescence, or positive post-treatment estimates ($\beta_{t\geq 0} > 0$) if incumbents benefit from new-skilled workers via, for example, learning or q-complementarity between occupational incumbents and new-skilled entrants.

We estimate the regression separately for incumbent workers of different age groups (with age measured in $t = 0$): 24–34, 35–44, 45—54, and 55–65 years old. 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, resulting in a sample of 673,555 unique workers in the treated group and 548,250 in the control group (who can be used as controls in multiple events). As before, control group workers are weighted by $1/n_i$, with n_i the number of controls for treated worker i.

Appendix Table B15 shows descriptives for the stacked sample of occupational incumbents. On average, incumbents are 43 years old, 23–26% are female, and they earn around

113–117 euros daily— 50% more than the early career workers we considered earlier. Unsurprisingly, incumbents are somewhat less likely to switch occupations, industries, and firms than are early career workers.

Findings. Panel A of Figure 19 shows that curriculum updates negatively affect wages for older occupational incumbents (ages 35 and older, but especially ages 55–65), consistent with skill obsolescence. These wage losses are sizable, and cumulate over time: after five years, daily wages fall by 2.2% for incumbents aged 35–44, 3.3% for incumbents aged 45–54, and 9.7% for incumbents aged 55–65. These wage losses experienced by older workers inform about pure skill price changes, since older workers are unlikely to upgrade their skills on the job (Heckman et al., 1998; Bowlus et al., 2023). For the youngest incumbents, we do not find wage losses: wage effects are small and positive but not statistically significant for those aged 24–34. Panel B of Figure 19 shows that incumbents do not work fewer days a year in response to the entrance of new-skilled workers. However, reductions in daily hours (i.e., moves to part-time work) would be captured in our daily wage effects shown in panel A. Moreover, we focus on incumbents who worked full-time in the five years prior to the curriculum update and therefore likely have high labor force attachment.

Appendix Figure 20 shows that our results are robust to controlling for occupations' technology exposure based on the old curriculum, though wage effects become somewhat smaller in absolute size for the youngest and oldest age groups. For the youngest age group, we now find zero wage effects, while workers aged 55–65 lose 7.5% five years after the curriculum update. This is consistent with underlying technological change benefiting younger and harming older workers.

In contrast to new-skilled workers, incumbents— especially the younger ones— are *more* likely to switch 1-digit occupations or 1-digit industries, as shown in panels A and B of Figure 21. (Results are robust to considering more detailed occupation and industry classifications.) This suggests that new-skilled workers have skills relevant for the occupation they were trained in, reducing their occupation switching, while younger incumbents lack the expertise currently relevant in their occupation and respond by switching to other jobs. We also find that incumbents, especially older ones, are more likely to move to firms with lower AKM fixed effects, shown in panel C of Figure 21. Our findings are consistent with Janssen and Mohrenweiser (2018), who study the effect of a single curriculum update involving CNC skills on incumbents, finding sizable wage losses coupled with increased occupational mobility (and only small and transitory non-employment effects).

These analyses contribute causal evidence of skill obsolescence. Our findings align with Deming and Noray (2020)'s cross-sectional analysis of STEM workers, showing flattening age-earnings curves and increased job switching over worker careers for faster-changing educational fields.

4.4 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. 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 key 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 for all employees at surveyed firms on June 30 of each year. 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, restricting the sample to firms with at least one trainee in at least one year. 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 vocational training occupations (in terms of pre-update trainee employment share).[38]

We estimate a stacked-event DiD model at the firm level:

$$Y_{ft} = \sum_{t=[-5,5]} \beta_t \text{Update}_f \times I_t + \delta_f + \gamma_t + \varepsilon_{ft}, \tag{7}$$

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

where Y_{ft} is log investments for firm f in year $t = [-5, 5]$. Time t is normalized such that $t = 0$ 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_t calendar year fixed effects. As before, all indices refer to the index by event. We retain firms that are observed for at least three years and invest at least once in the time window and match firms on log investment levels in the pre-treatment periods ($t-1$ to $t-5$) using Mahalanobis distance matching (selecting the three nearest-neighbors). 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.

Table 10 shows firm-level descriptives for treated and control firms in year $t-1$, post matching. Our analyses are based on an unbalanced panel of 2,589 distinct firms in $t \leq -1$, with 1,429 treated. Treated firms employ an average of 587 workers (389 for control firms), and are more likely to be in the manufacturing sector. Log investments have a high standard deviation of around 2.2, reflecting that investments are lumpy. Around 86% of treated and control firm observations report positive investments, with average log investments of 6.83 annually for treatment firms and 6.53 for control firms.

Panel A of Figure 22 shows the estimates. Log investments rise in treated versus control firms in the first two years apprentices are trained in the new curriculum, with investment increases of 7.3% in the first and 13.0% in the second year, corresponding to 3.3% and 5.9% of a standard deviation. In Appendix E, we also show that the number of apprenticeship positions increase for updated curricula compared to those without updates, which may require additional investments. This suggests that both the need to train new skills and newly supplied skills raise firm investments. Consistent with this interpretation, these investment increases are mostly observed for curriculum updates with high technology exposure, as seen in panel B of Figure 22.

The co-movement of skill supply and capital investment highlights the complementarity between human and physical capital, especially in jobs with high technology exposure.

5 Conclusion

Advancing technology reshapes skill demands: can changes in educational content enable workers to adapt? We examine this question using vocationally trained workers in Germany, a large population of non-college workers 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, we establish four main findings. First, technological breakthroughs 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, highlighting that workers acquire new competences. Strikingly, within-occupation skill adjustments driven by curriculum updates account for two-thirds of the aggregate decline in routine task content of vocational occupational skill supply, paralleling previous findings that within-occupation task changes dominate aggregate skill demand shifts.

Third, curriculum updates generate significant returns for 'new-skilled' workers. Labor market entrants trained under updated curricula earn 3.3% 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 relative gains from deteriorating outcomes for control groups. The benefits concentrate among curriculum updates with high technology exposure, suggesting that aligning training content with technological change keeps workers' labor market expertise relevant.

Fourth, skill updates create winners and losers. Older incumbent workers (ages 55–65) experience wage declines of up to 9.7% when new-skilled workers enter their occupation, consistent with skill obsolescence. Younger incumbents do not experience substantial wage declines but respond by switching occupations. Consistent with technology's important role in demanding new skills, firms exposed to workers trained in updated curricula increase capital investments, especially for technology-intensive curriculum updates. This is 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 human expertise as technology advances. 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. The rapid progress of artificial intelligence only reinforces these points.

Educational content updates occur beyond Germany, and the German vocational system setting offers broader lessons. Curriculum updates in Germany result from negotiations among employer organizations, labor unions, and the Federal Institute for Vocational Education and Training. Recent work suggests that employer involvement may be important for ensuring skills remain labor-market relevant (Katz et al., 2022; Dillon et al., 2025). Further, coordination among employers through legally binding curricula may increase costly training investments in new skills. Absent such coordination, individual firms fearing poaching may be less inclined to provide training—we show that firms indeed increase apprenticeship positions following curriculum updates. Benefits for workers are potentially strengthened by the active role of labor unions and the Federal Institute for Vocational Training in curriculum updates, since they emphasize that skills covered in the curriculum 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.

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Figures

Figure 1: Distribution of Wages for Occupations With and Without Vocational Training Curriculum

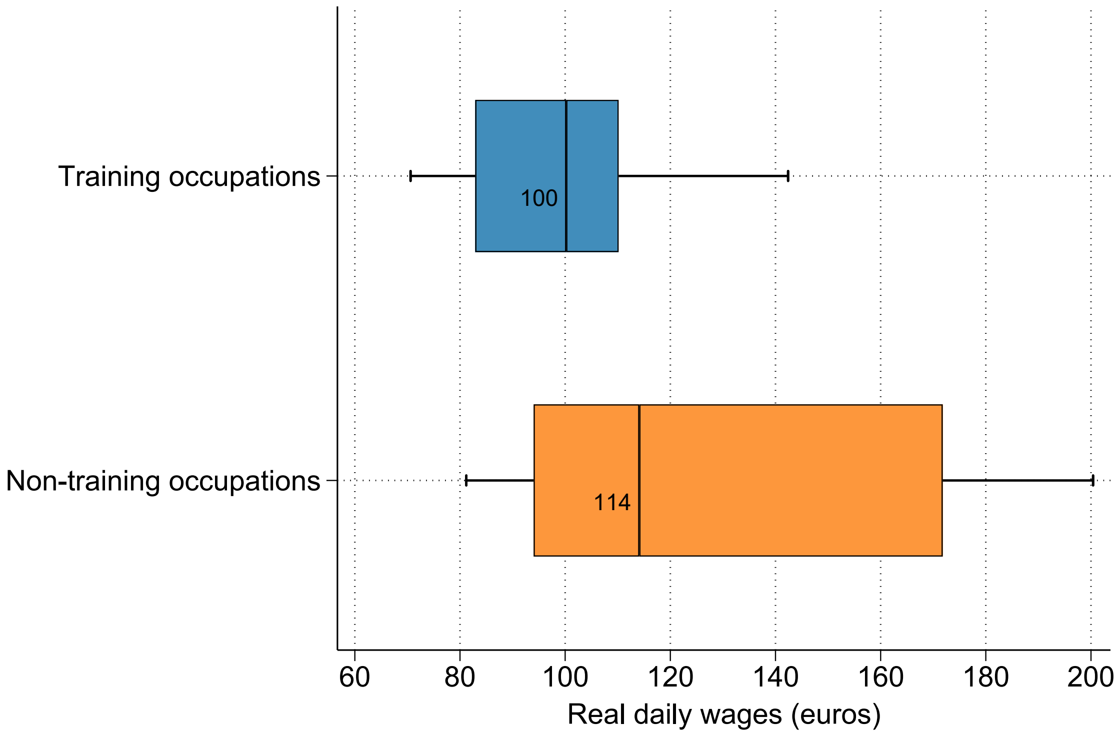


Figure shows a boxplot of real daily wages for occupations with and without a vocational training curriculum (base year for deflation: 2015) based on SIAB data. Vertical lines indicate the median; boxes reflect the interquartile range; and whiskers indicate the 10th and 90th percentiles. Occupations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

Figure 2: 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 3: 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 4: 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 5: 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

[...]

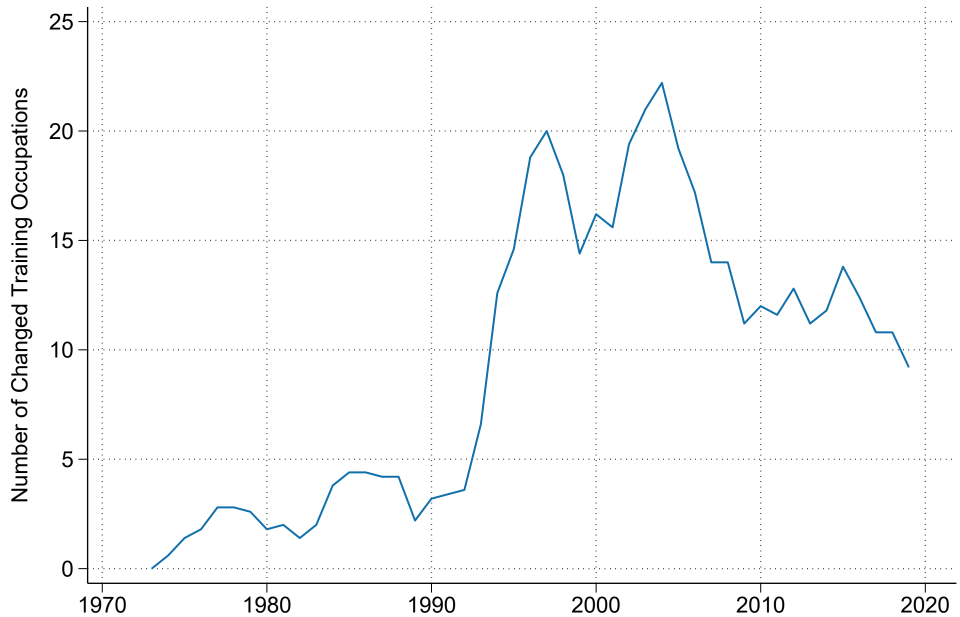
[...] the examinee must handle processes and complex issues in case studies (...) and show that he can analyze business processes and develop problem-solving solutions in a result-and costumer-oriented manner.

[...]

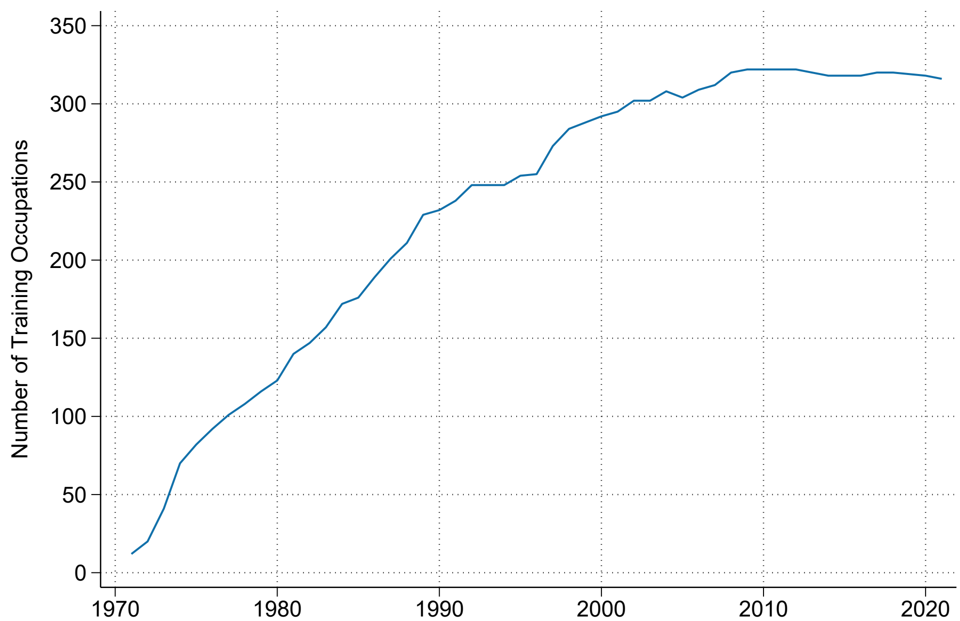
No.	Part of the apprenticeship profile	Knowledge and skills to be imparted
3.2	Information and communication systems (§4 Para. 1 No. 3.2)	[...] d) Using the operating system, standard software and company-specific software e) Entering data and information [...]
3.3	Planning and Organization (§4 Para.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

Figure 6: Curriculum Updates Over Time

A. Number of Curriculum Changes by Year



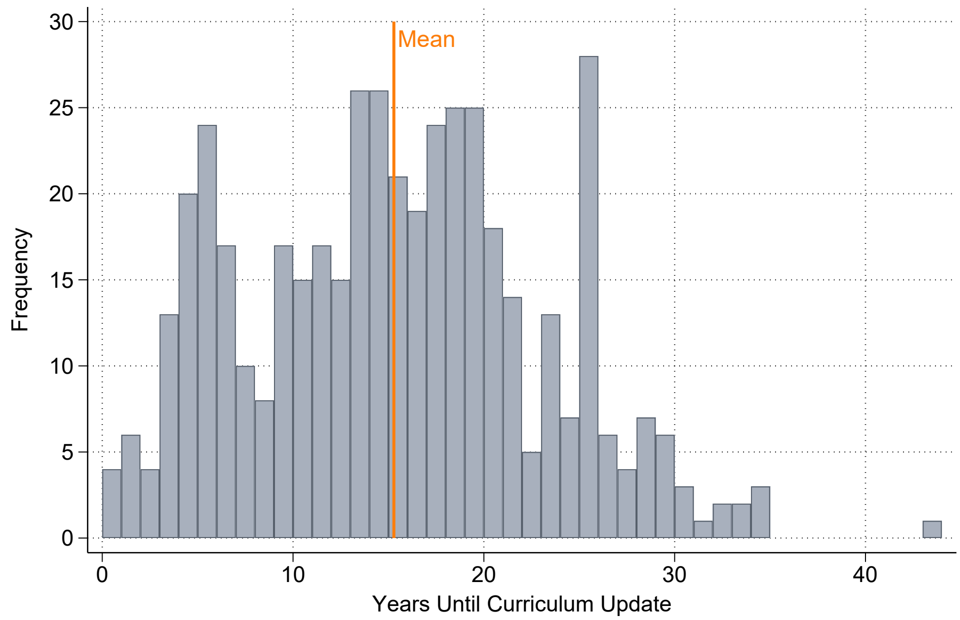
B. Number of Training Occupations with Observed Curriculum by Year



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 7: Years until Curriculum Update

A. Overall



B. By Broad Occupation Group

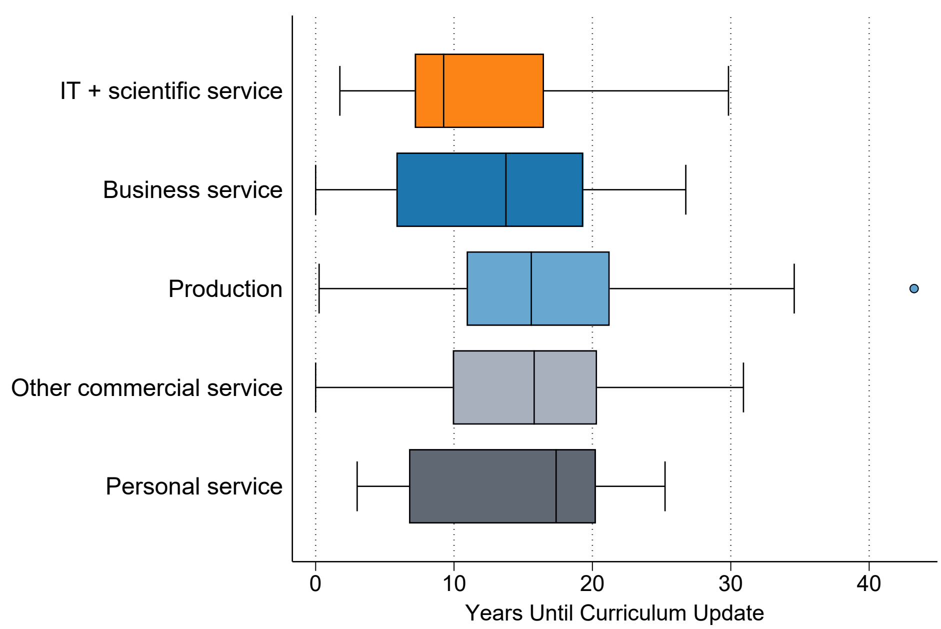


Figure shows the distribution of years until curriculum updates for initial training occupation observations ($N = 470$). Panel A shows the overall distribution across training occupations. Panel B shows a boxplot by broad occupation group. Vertical lines indicate the median; boxes reflect the interquartile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

Figure 8: Share of Breakthrough Patents by Technology Class

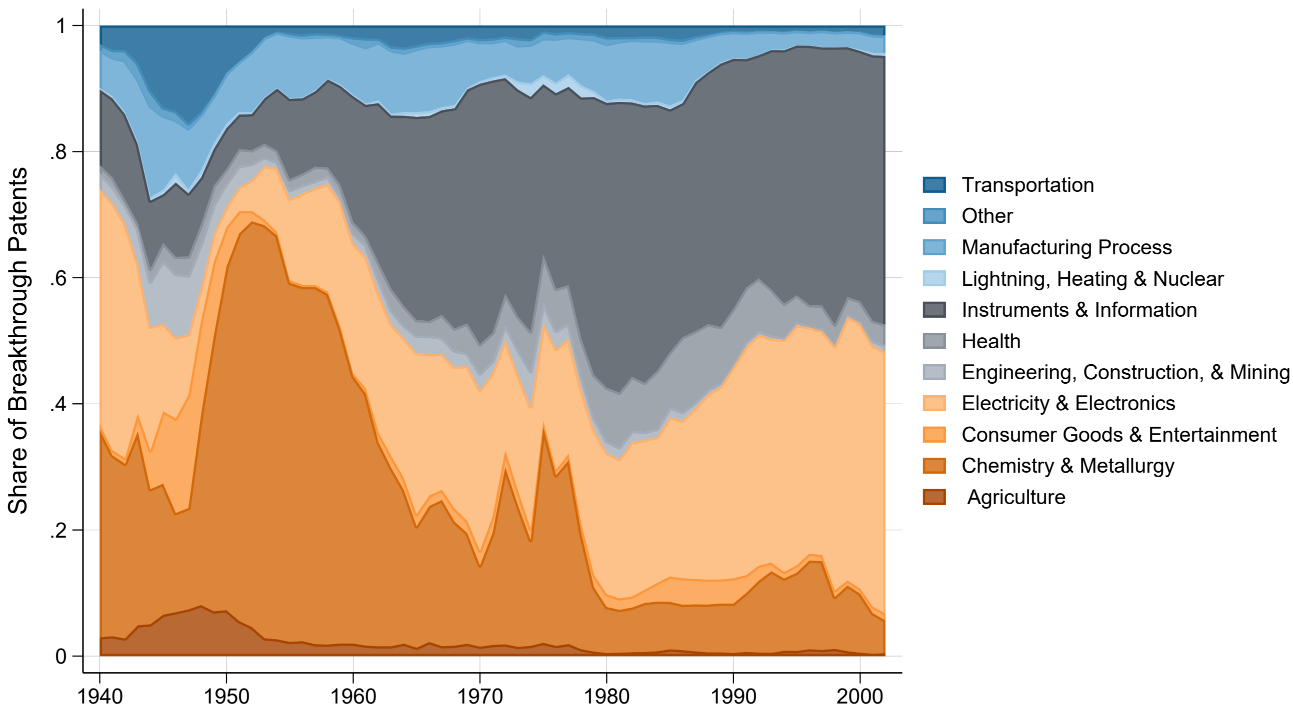
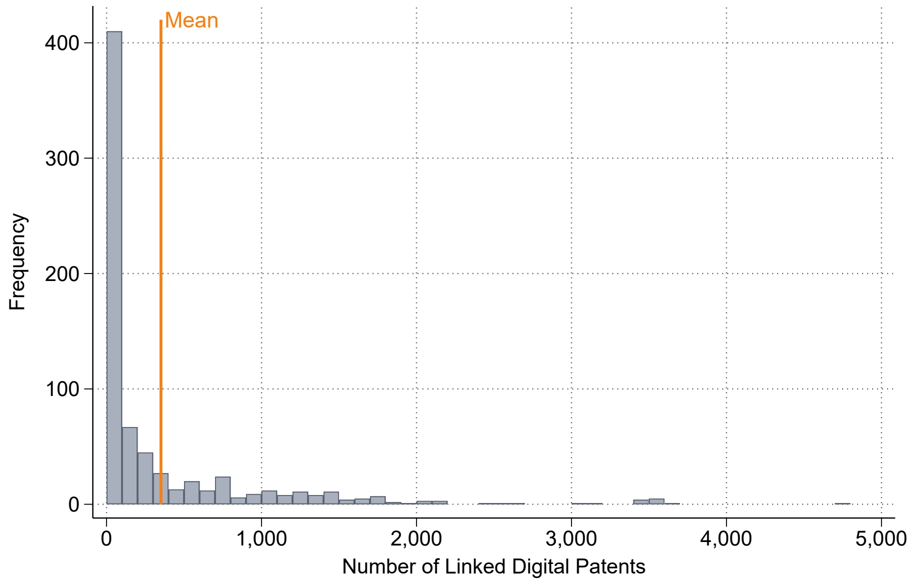


Figure shows the distribution of breakthrough patents across broad technology classes defined by Kelly et al. (2021). Over 1940–2002, we observe $N = 141,708$ breakthrough patents in Instruments & Information.

Figure 9: Digital Technology Exposure of Training Curricula

A. Overall



B. By Broad Occupation Group

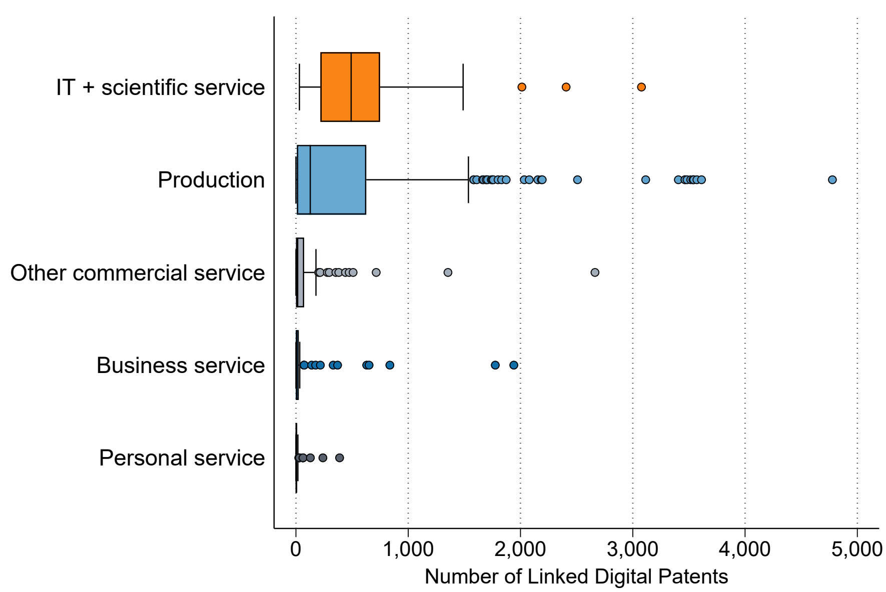


Figure shows the distribution of linked digital patent counts for initial training occupation observations ($N = 791$). Panel A shows the overall distribution across training occupations. Panel B shows a boxplot by broad occupation group. Vertical lines indicate the median; boxes reflect the interquartile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

Figure 10: Curriculum Survival Rates by Technology Exposure

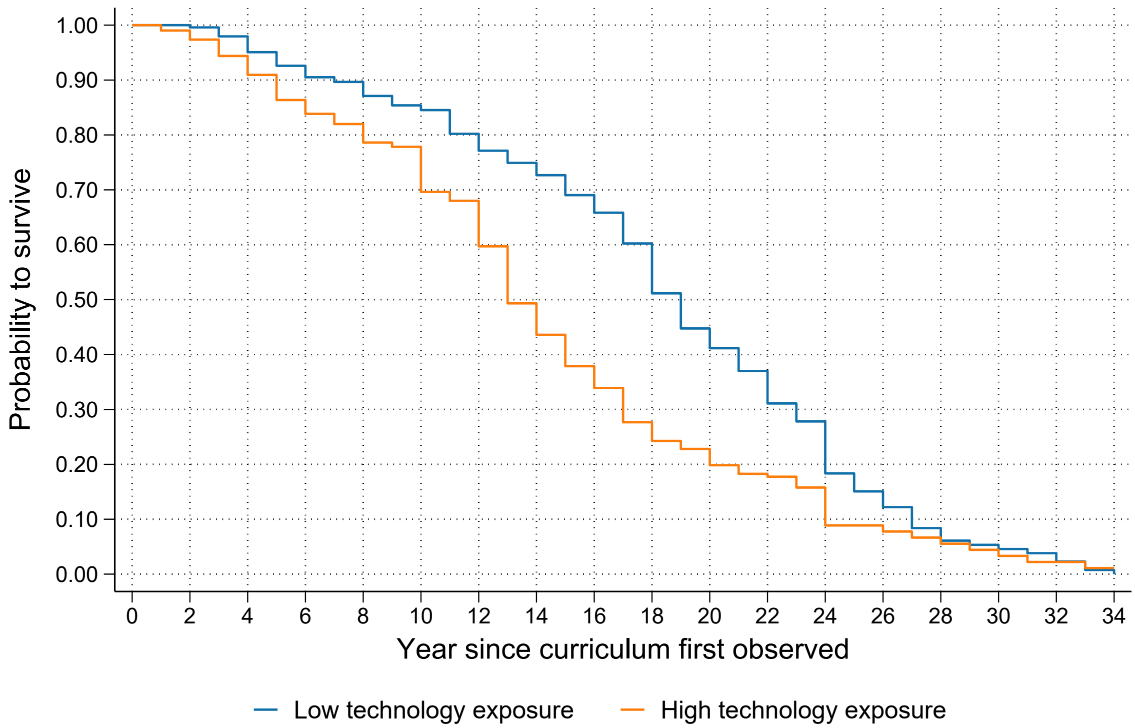


Figure shows Kaplan-Meier survival curves for all curricula updated at some point over the 1970–2021 period, separately by technology exposure. Low technology exposure is below-median exposure; high technology exposure is at or above median exposure.

Figure 11: Impacts of Digital Technology Exposure on Curriculum Updates Using Local Projections

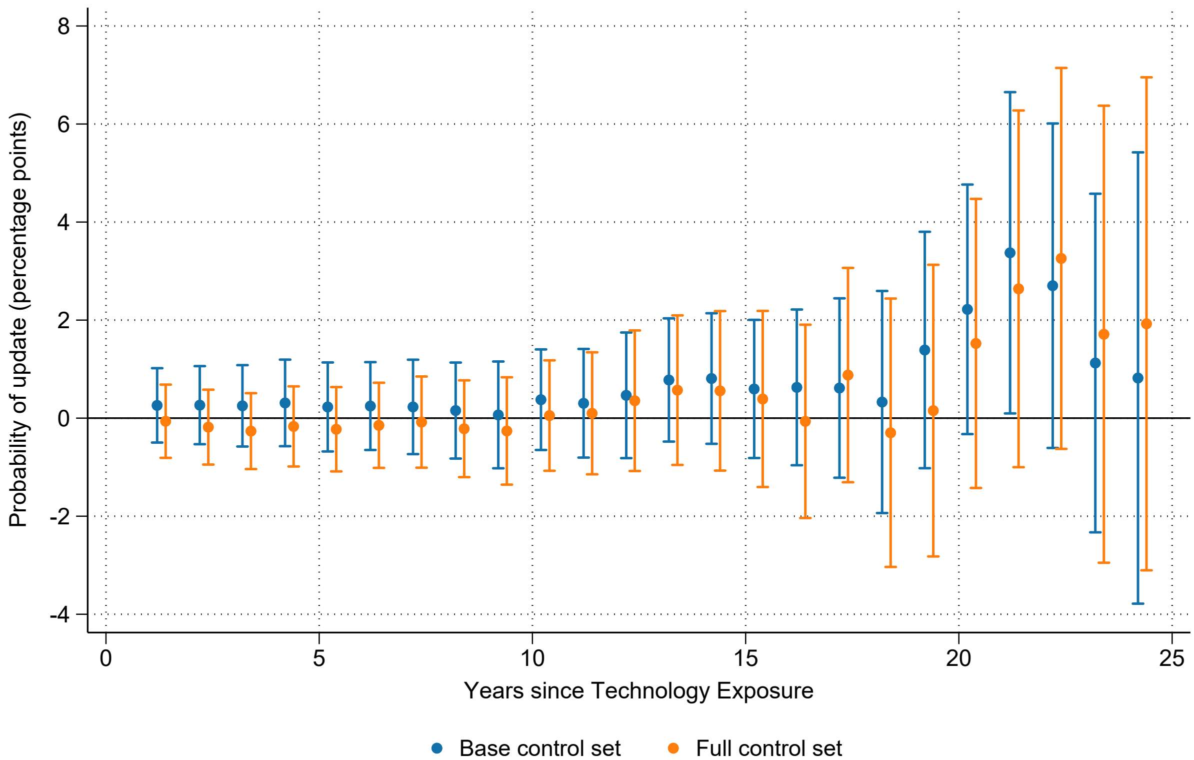


Figure presents estimates of equation (3). The dependent variable is a dummy for the curriculum being updated (conditional on not having being updated yet). Coefficients multiplied by 100. Standard errors clusted by occupation, whiskers represent 95% confidence intervals.

Figure 12: Changes in Digital Technology and Social Skill Use in Updated Curricula, 1976–2021

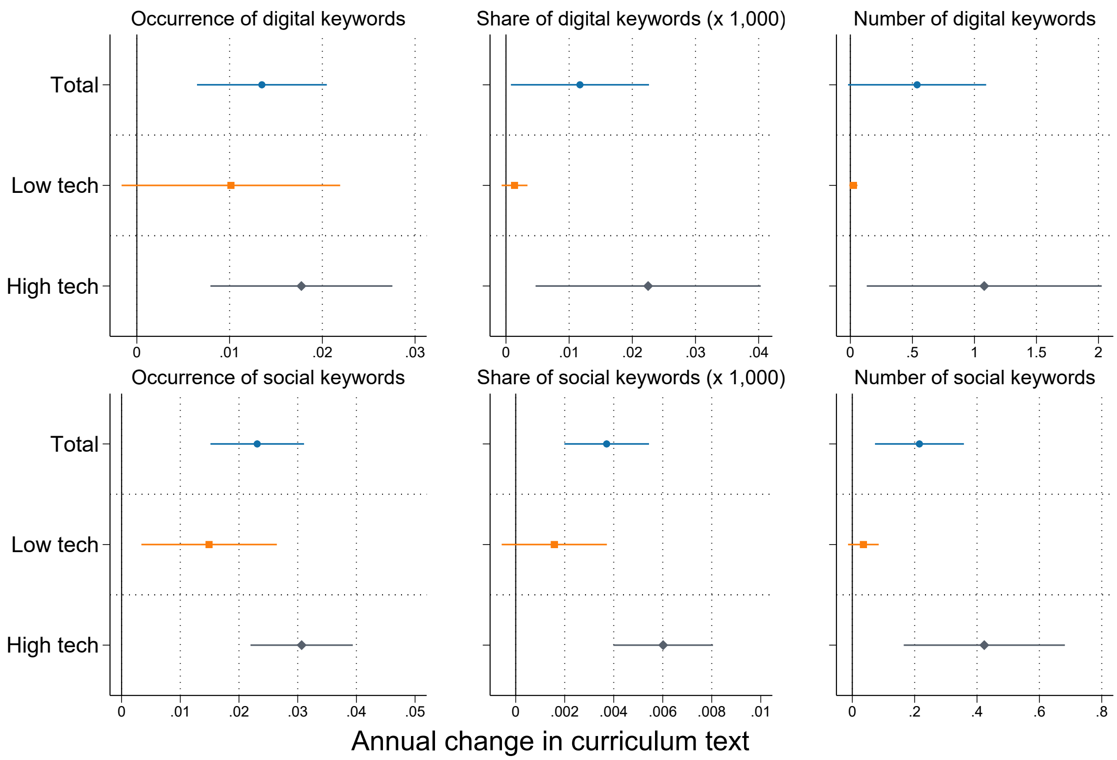


Figure reports coefficients on a linear timetrend, from a regression of keyword occurrence, keyword shares, or keyword counts in vocational training curricula (see equation (4)), for the subsample of curricula with updates over 1976–2021. High tech (low tech) defined as curricula with an initial digital technology exposure above (at or below) the median across all occupations.

Figure 13: Changes in Routine Task Intensity in Updated Curricula, 1976–2021

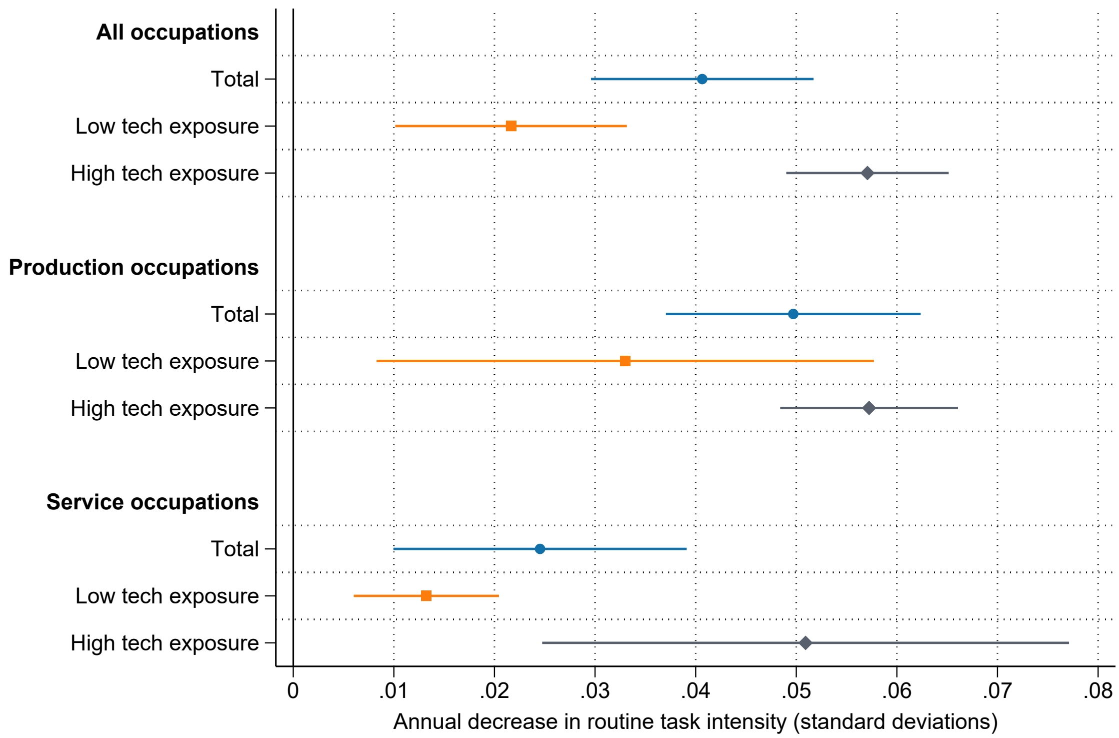


Figure reports coefficients on a linear timetrend, from a regression of routine task content in vocational training curricula (see equation (4)), for the subsample of curricula with updates over 1976–2021. Horizontal lines reflect 95% confidence intervals. High tech (low tech) defined as curricula with an initial digital technology exposure above (at or below) the median across all occupations.

Figure 14: Changes in Curriculum Non-Routine Task Intensity from Removed, Remaining, and Newly Added Words

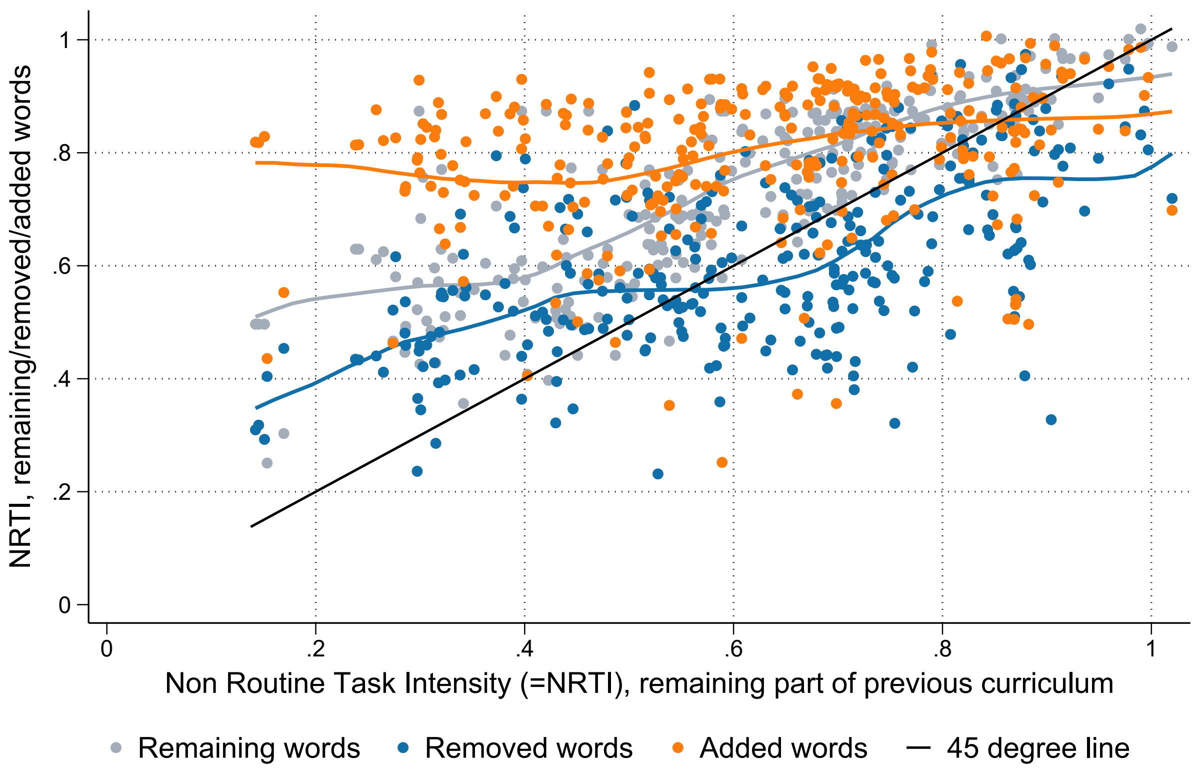
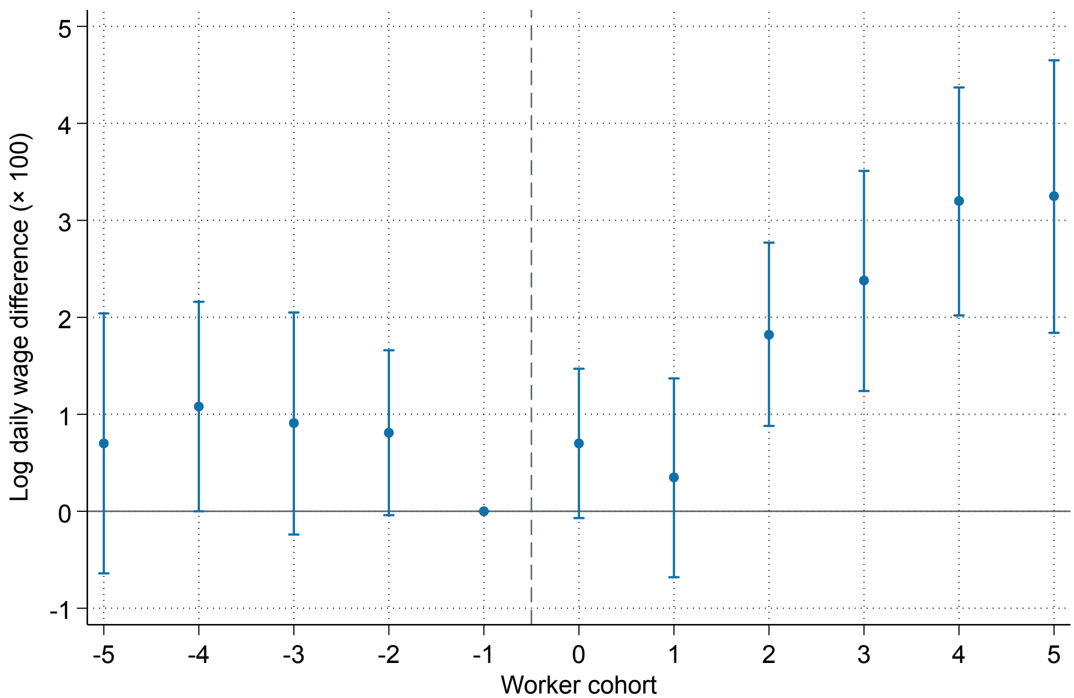


Figure presents the non-routine task intensity of new curriculum words plotted against remaining words in the previous curriculum. Fitted lines are local polynomials weighted by training occupation employment shares.

Figure 15: Wage and Earnings Impacts of Curriculum Updates

A. Log Daily Wages



B. Log Annual Earnings

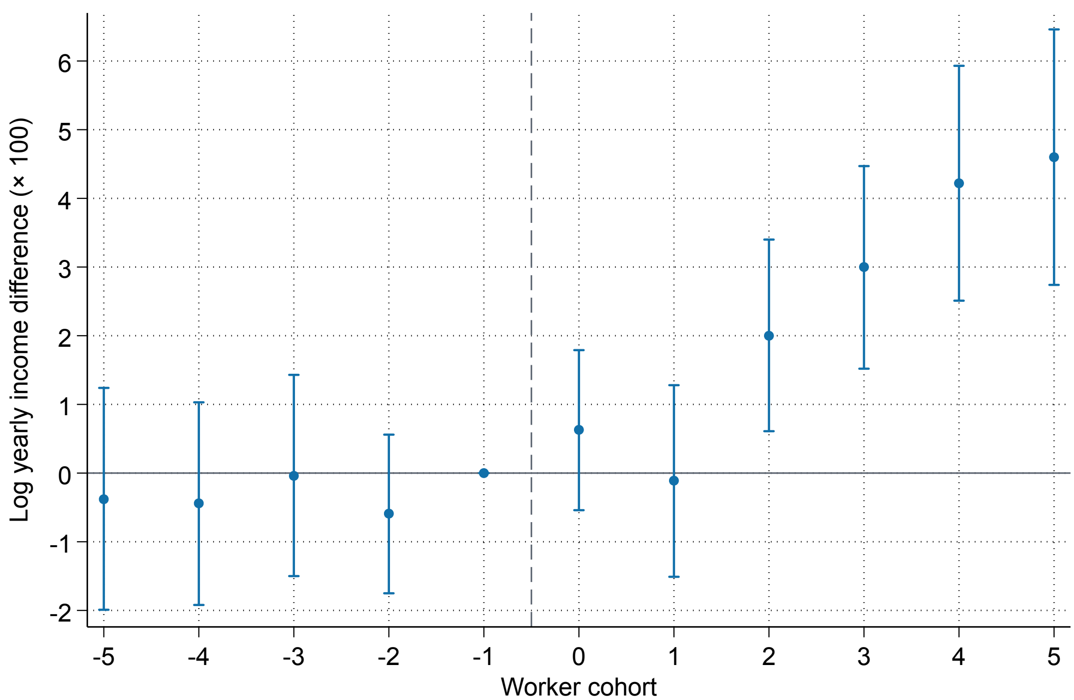
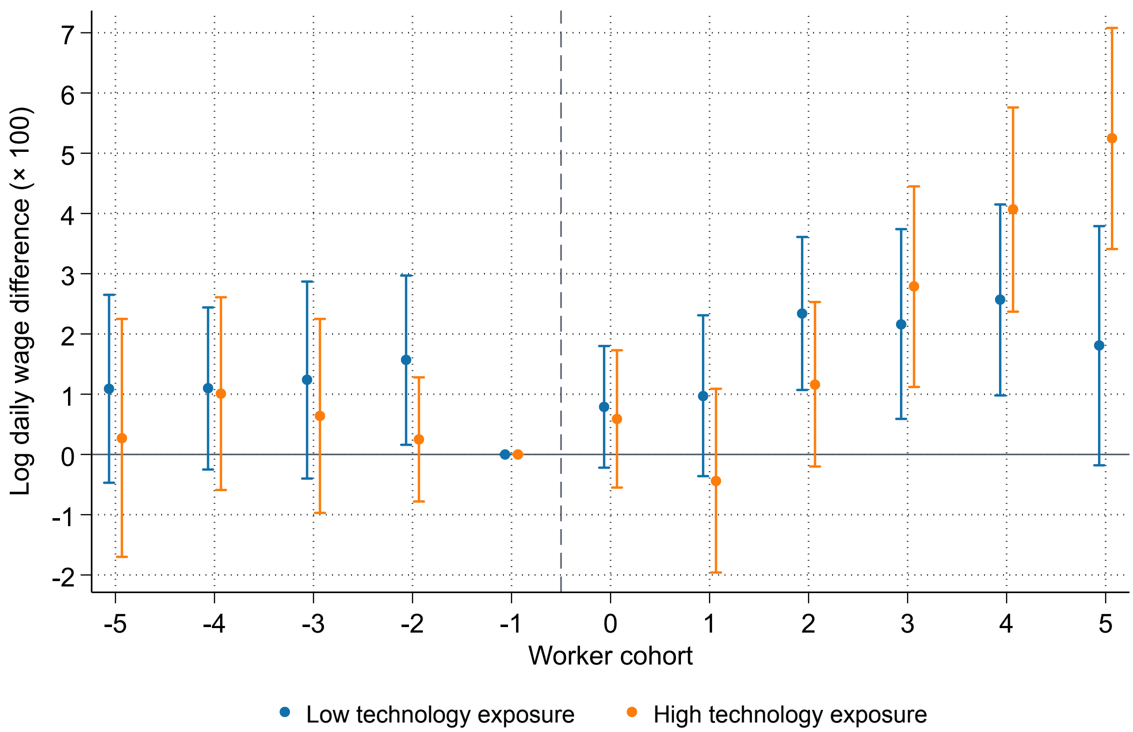


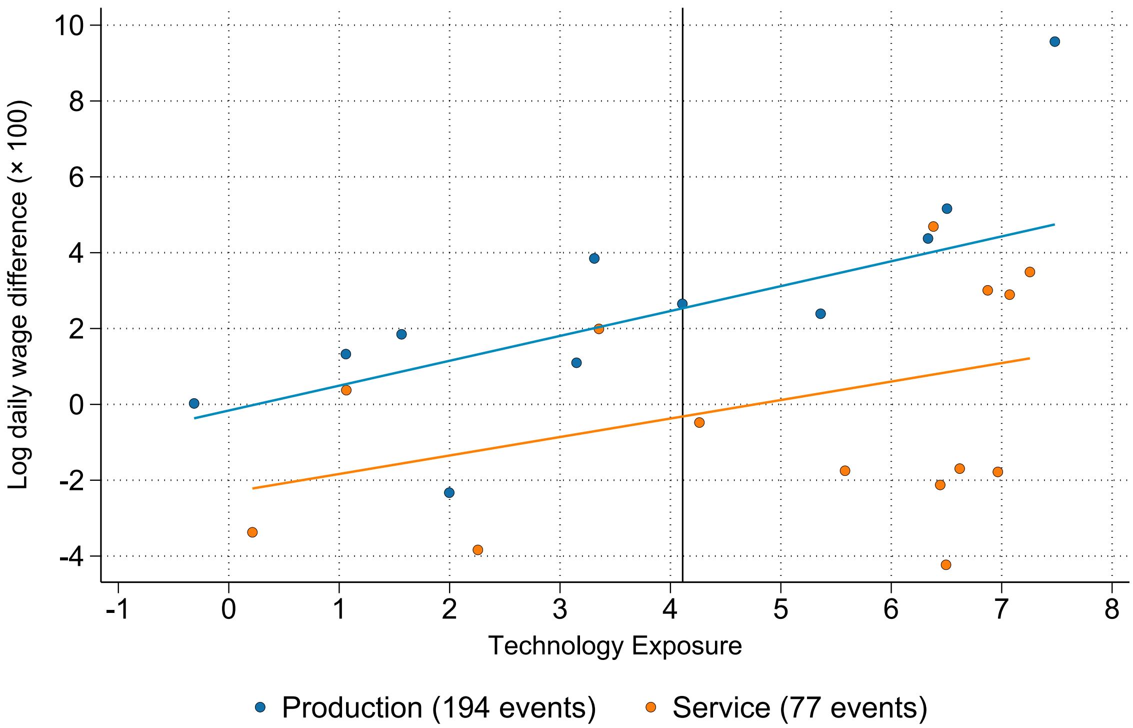
Figure reports stacked difference-in-differences estimates of equation (5), and 95% confidence intervals. Cohort 0 is the first cohort with the new curriculum, cohort -1 is the reference category. Individuals are included up to five years after graduation. Standard errors clustered at the level of occupation by event. $N = 7,719,765$ for panel A and $N = 8,966,826$ for panel B; 375 events for both panels.

Figure 16: Wage Impacts of Curriculum Updates by Technology Exposure



Stacked difference-in-differences estimates of equation (5), 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. $N = 4,029,336$ for low exposure (175 events), and $N = 3,670,190$ for high exposure (182 events).

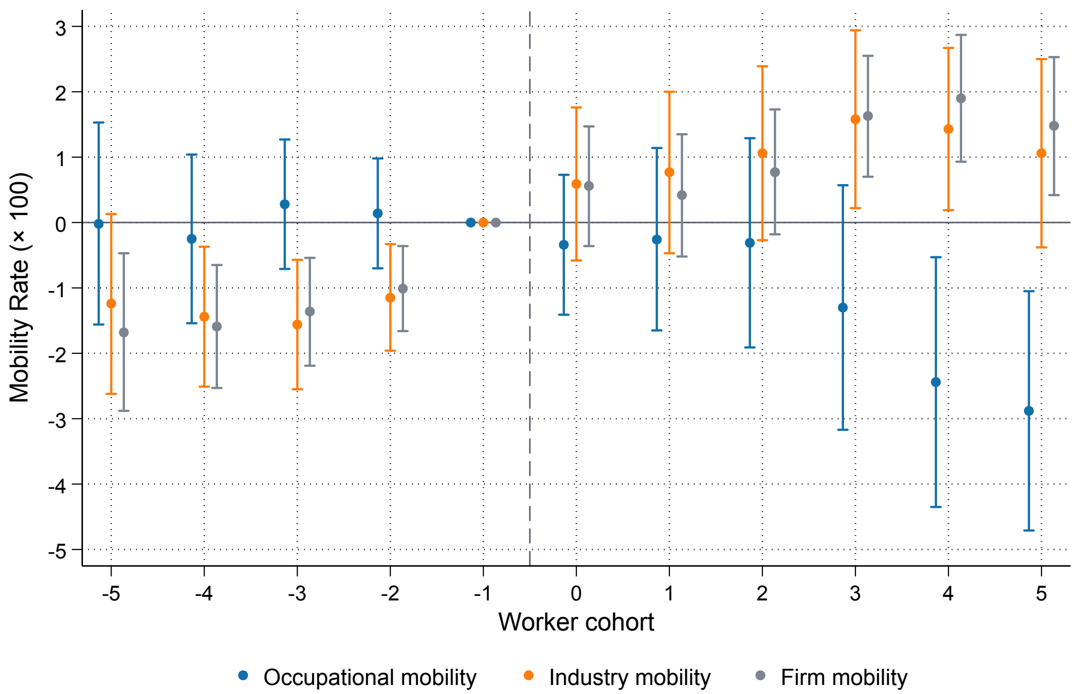
Figure 17: Update-Specific Wage Impacts by Curriculum Technology Exposure



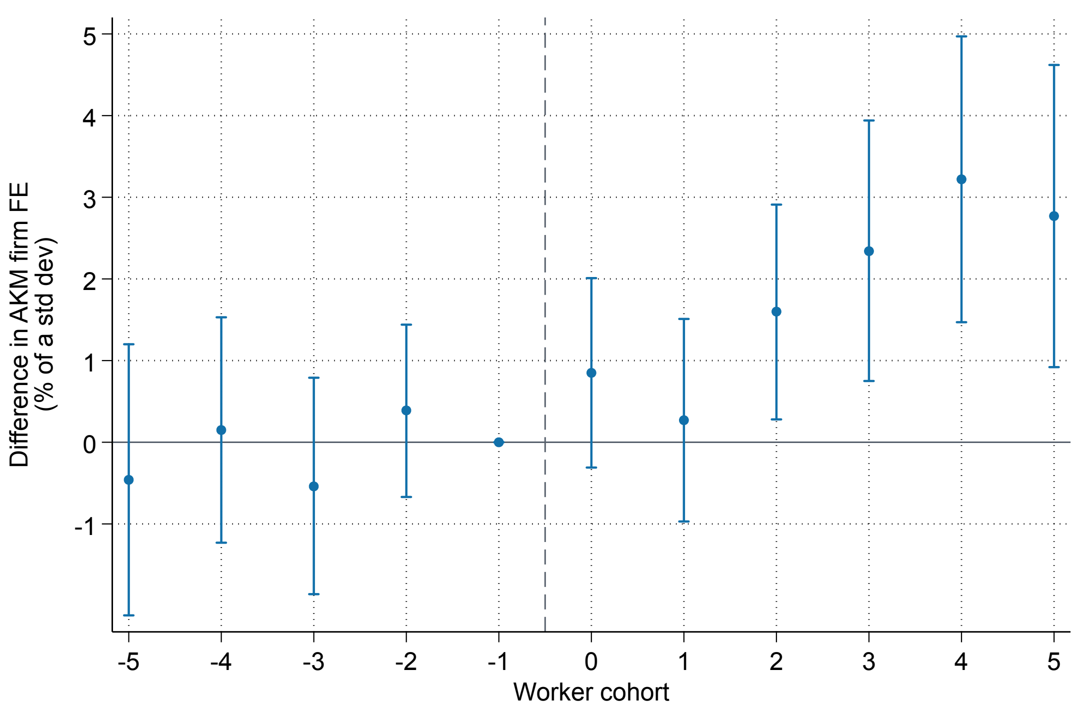
Binscatter of wage returns estimated separately for each curriculum update event, against curriculum technology exposure, measured as the log of linked patents. The vertical line indicates median technology exposure as used throughout the paper.

Figure 18: Worker Mobility Impacts of Curriculum Updates

A. Occupation, Industry, and Firm Mobility



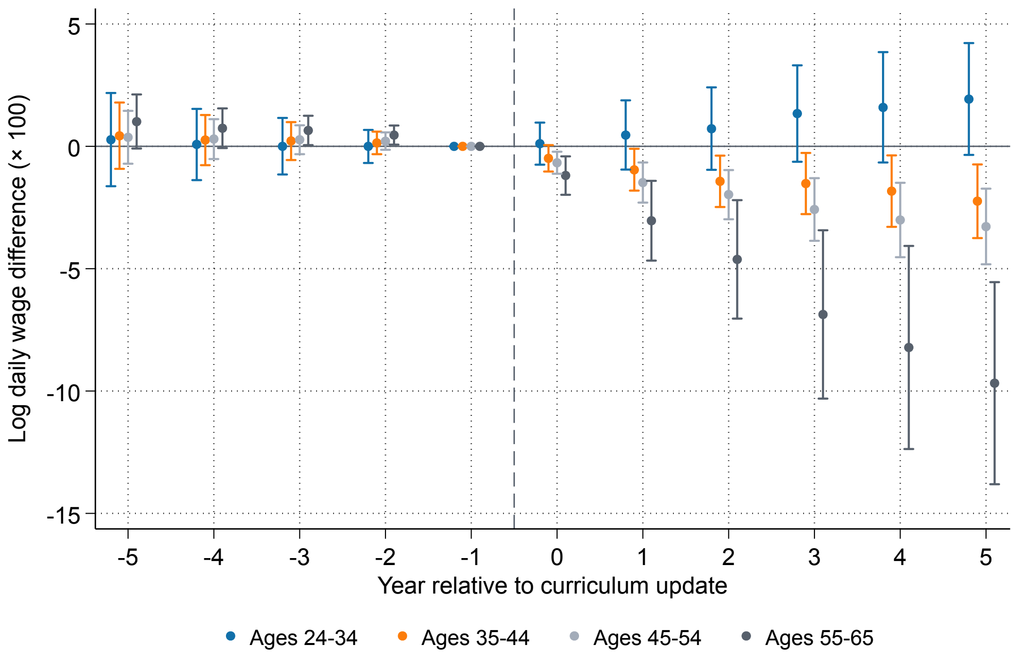
B. Firm AKM Fixed Effects



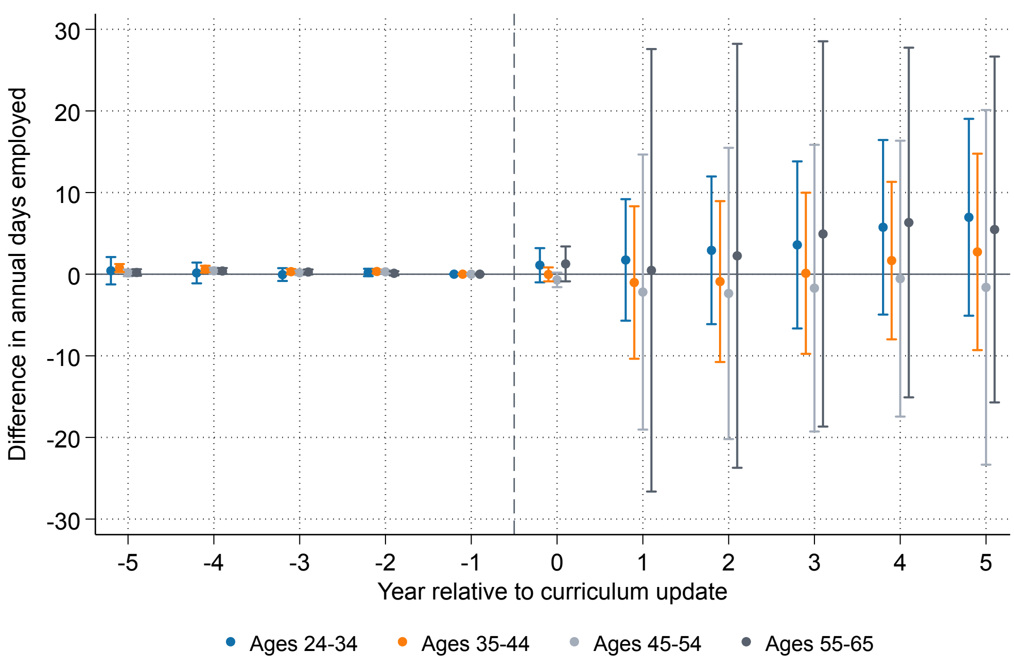
Stacked difference-in-differences estimates of equation (5), and 95% confidence intervals. Mobility is defined relative to the apprenticeship position in panel A. Cohort 0 is the first cohort with the new curriculum; cohort -1 is the reference category. Individuals are included up to five years after graduation. Standard errors clustered at the level of occupation by event. Panel A: $N = 9,011,655$; Panel B: $N = 8,878,251$.

Figure 19: Wage and Employment Impacts of Curriculum Updates for Occupational Incumbents

A. Log Daily Wage

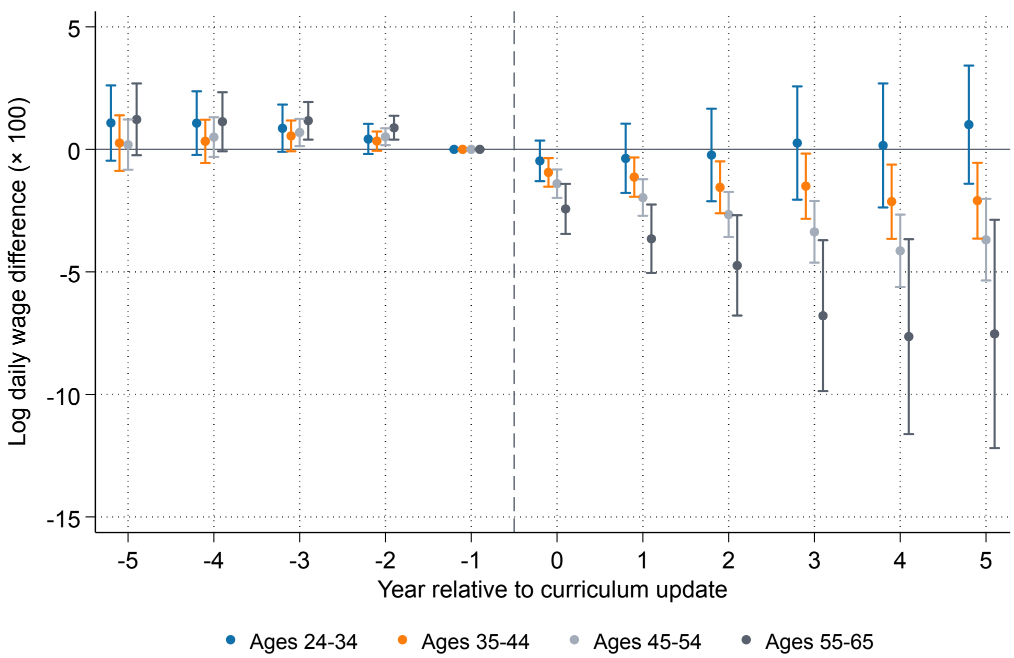


B. Annual Days of Employment



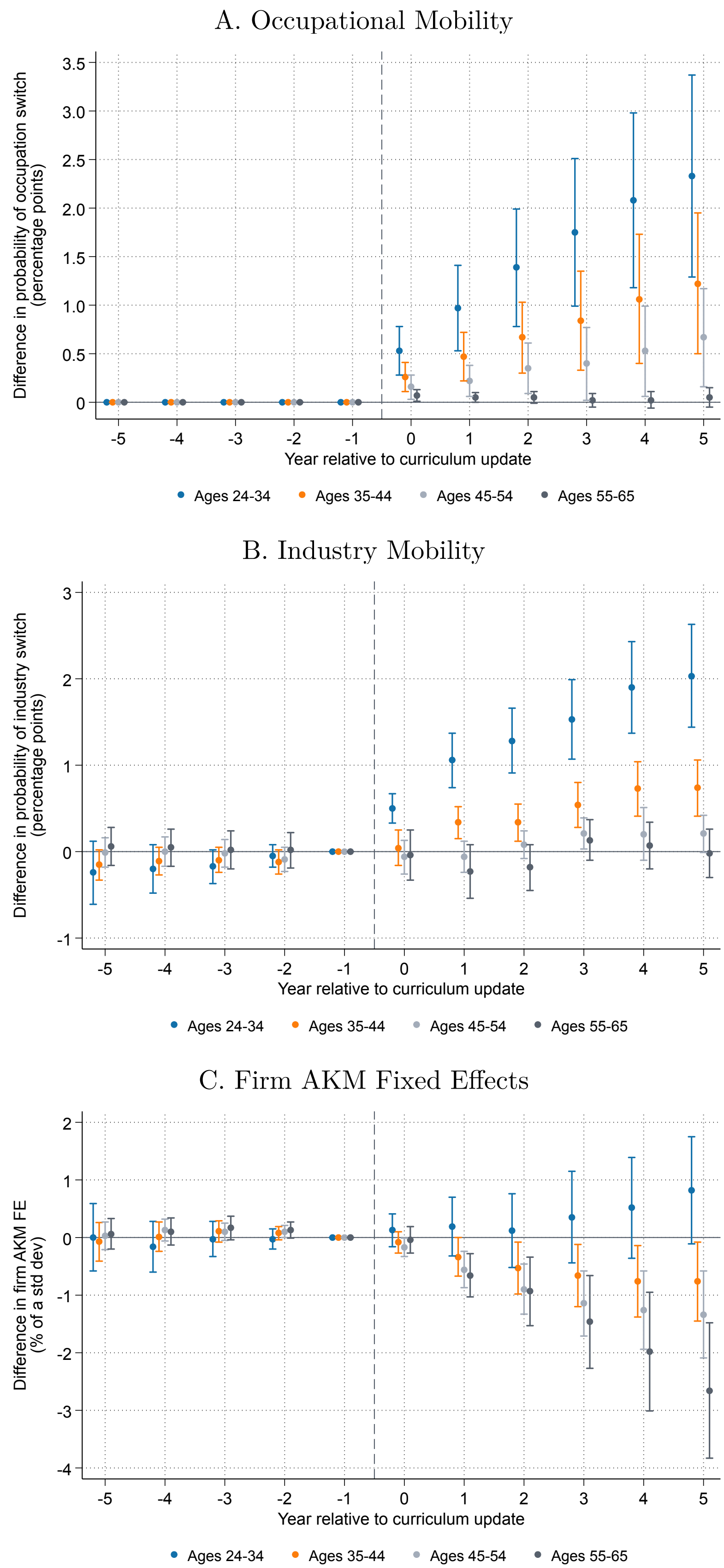
Stacked difference-in-differences estimates of equation (6), and 95% confidence intervals. Based on 420 curriculum update events for both panels. Panel A: $N_{24-34} = 4,715,363$, $N_{35-44} = 7,625,523$, $N_{45-54} = 6,676,771$, $N_{55-65} = 2,453,266$; Panel B: $N_{24-34} = 5,298,332$, $N_{35-44} = 8,232,520$, $N_{45-54} = 7,438,999$, $N_{55-65} = 3,135,976$.

Figure 20: Wage Impacts of Curriculum Updates for Occupational Incumbents, Controlling for Prior-Curriculum Technology Exposure



Stacked difference-in-differences estimates of equation (6), and 95% confidence intervals. Technology exposure of the prior curriculum is defined as the log number of (lagged) digital breakthrough patents linked to the occupation's curriculum in $t = -1$. Based on 420 curriculum update events, $N_{24-34} = 2,854,368$, $N_{35-44} = 4,673,609$, $N_{45-54} = 4,096,838$, $N_{55-65} = 1,535,489$.

Figure 21: Job Mobility Impacts of Curriculum Updates for Occupational Incumbents

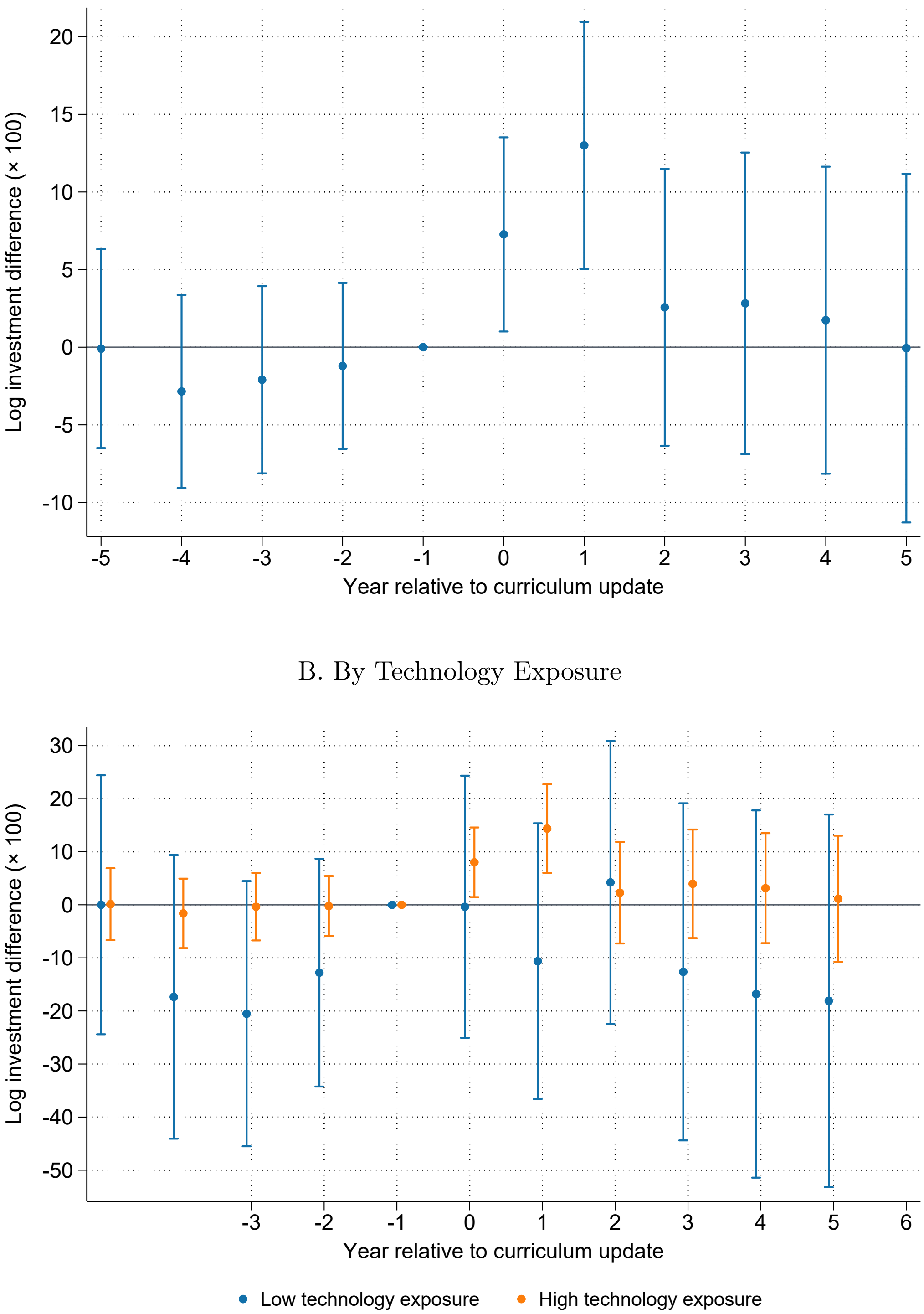


Stacked difference-in-differences estimates of equation (6), and 95% confidence intervals. Based on 420 curriculum update events for all panels. Panel A: $N_{24-34} = 3,002,679$, $N_{35-44} = 4,605,427$, $N_{45-54} = 3,944,682$, $N_{55-65} = 1,233,546$; Panel B: $N_{24-34} = 4,728,882$, $N_{35-44} = 7,633,285$, $N_{45-54} = 6,687,258$, $N_{55-65} = 2,461,615$; Panel C: $N_{24-34} = 4,694,067$, $N_{35-44} = 7,587,532$, $N_{45-54} = 6,636,704$, $N_{55-65} = 2,435,737$.

Figure 22: Investment Impacts of Curriculum Updates

A. Overall

B. By Technology Exposure



Stacked difference-in-differences estimates of equation (7) using log investments as the dependent variable, and 95% confidence intervals. Based on 262 curriculum update events, $N = 71,188$ in Panel A. In Panel B, $N = 6,363$ for low exposure (51 events), and $N = 63,526$ for high exposure (204 events).

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	N	Mean	SD	N
Any update	0.038	0.192	11,843	0.051	0.220	11,709
Type of update:						
Content update only	0.021	0.143	11,843	0.025	0.155	11,709
Content update + renaming	0.015	0.123	11,843	0.023	0.149	11,709
Content update + aggregation	0.010	0.098	11,843	0.020	0.140	11,709
Content update + segregation	0.003	0.053	11,843	0.004	0.065	11,709
Years until update $\mid$ update $= 1^{\dagger}$	15.3	7.8	455	14.3	7.4	444

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. † – Based on initial observations only.

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 5 digit occupation. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table 6: 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 5 digit occupation. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table 7: 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 5 digit occupation. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table 8: Decomposition of the overall change in routine task content in vocational skill supply, 1976–2021

Total change	Within-occupation change	Between-occupation change	Share of within-occupation component
-0.947	-0.625	-0.322	66%

Decomposition of the total change in the routine task intensity between 1976 and 2021 across occupations into the within-occupation curriculum component, holding occupation shares constant, and the between-occupation component, holding curriculum content constant: $\Delta \text{RTI}_{1976,2021} = \sum_j \Delta \text{RTI}_{j,1976,2021}(w_{j,1976} + w_{j,2021})/2 + \sum_j \Delta w_{j,1976,2021}(\text{RTI}_{j,1976} + \text{RTI}_{j,2021})/2$, with w_j occupation's j trainee employment share in the respective year. Employment of vocational trainees with reasonable training durations in West Germany per occupation and year based on the SIAB. For years before we observe the occupation's first curriculum, we use the routine task intensity of the occupation's first observed curriculum. This arguably leads to a conservative estimate of the within-occupation component. In standard deviations.

Table 9: 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
Daily wage	70.17	29.79	71.44
Annual daily wage growth	0.33	6.94	0.07
Years of training	2.82	0.53	2.88
Typical years of training	2.98	0.40	3.00
Annual days employed	267.71	138.52	365.00
Annual labor earnings	18,249	13,611	18,367
Firm size	560.14	2,757.64	40.00
Job mobility, relative to apprenticeship:			
Occupation	0.34	0.48	0.00
Industry	0.40	0.49	0.00
Firm	0.58	0.49	1.00
Job mobility, year-to-year:			
Occupation	0.16	0.37	0.00
Industry	0.17	0.38	0.00
Firm	0.26	0.44	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 10: Descriptives of Stacked and Matched Firm Sample

	A. Treated		*B. Control*	
	Mean	SD	Mean	SD
Number of workers	586.6	1,591.5	388.5	684.3
Any investment (1/0)	0.86	0.34	0.88	0.32
Log(investments)	6.83	2.33	6.53	2.11
Absolute investments in €1,000	6,845	26,552	3,142	7,296
Manufacturing/service sector (1/0)	0.42	0.49	0.18	0.38
N unique firms	1,429		1,160	

Source: LIAB. For years $t \leq -1$.

Appendix

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A Appendix figures

A.1 Data and measurement

Figure A1: Distribution of Wages for Vocationally Trained Workers vs. Others

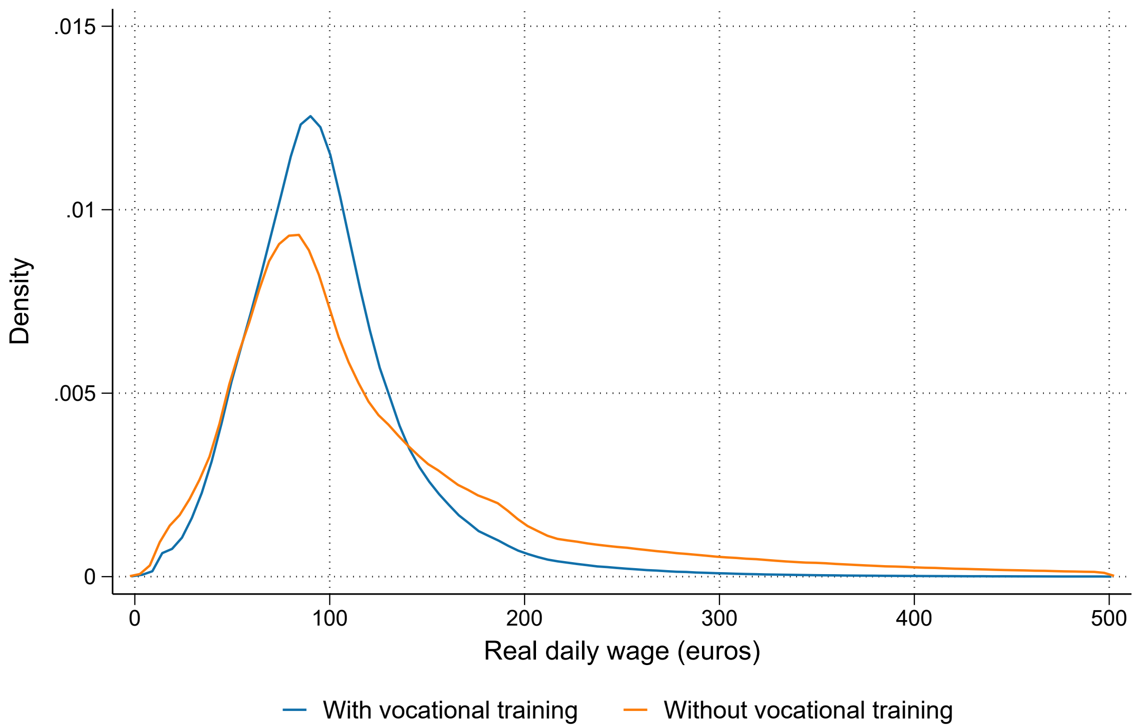
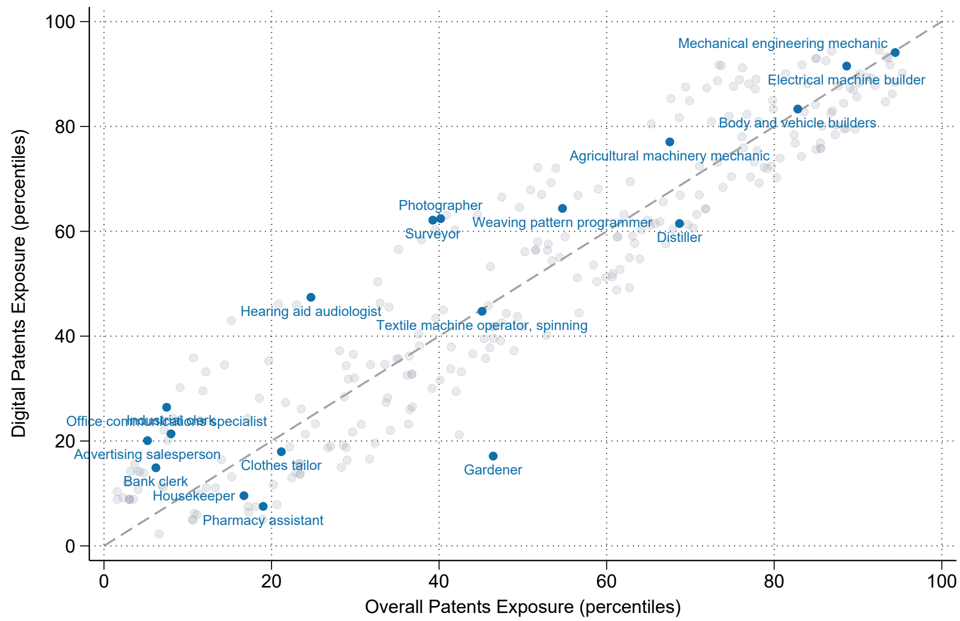


Figure plots the distribution of real daily wages (up to 500 euros) for vocationally trained workers versus all others based on SIAB data.

Figure A2: Digital and Overall Technology Exposure of Training Curricula

A. Average over 1971–1997



B. Average over 1998–2021

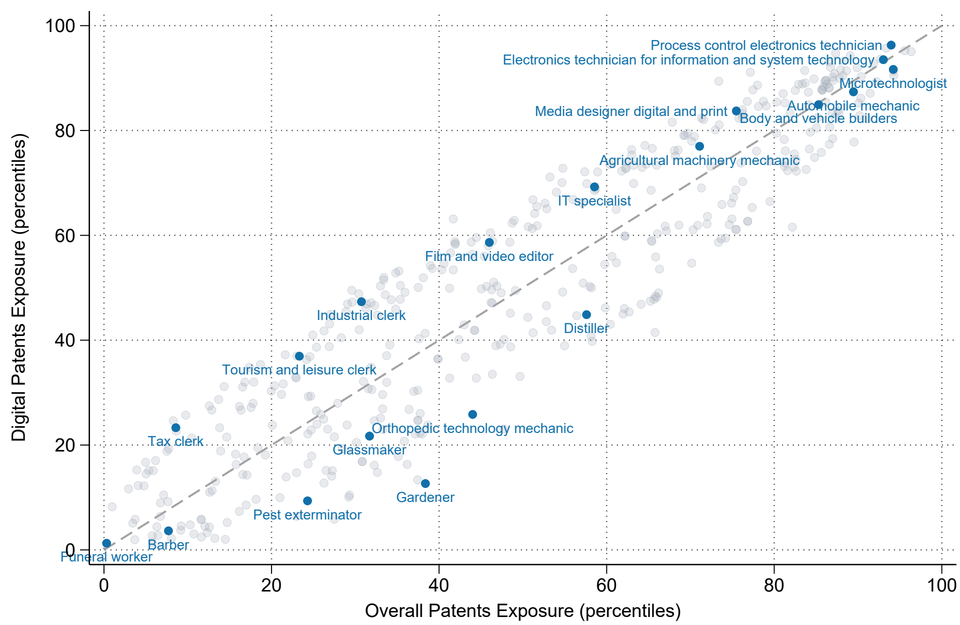
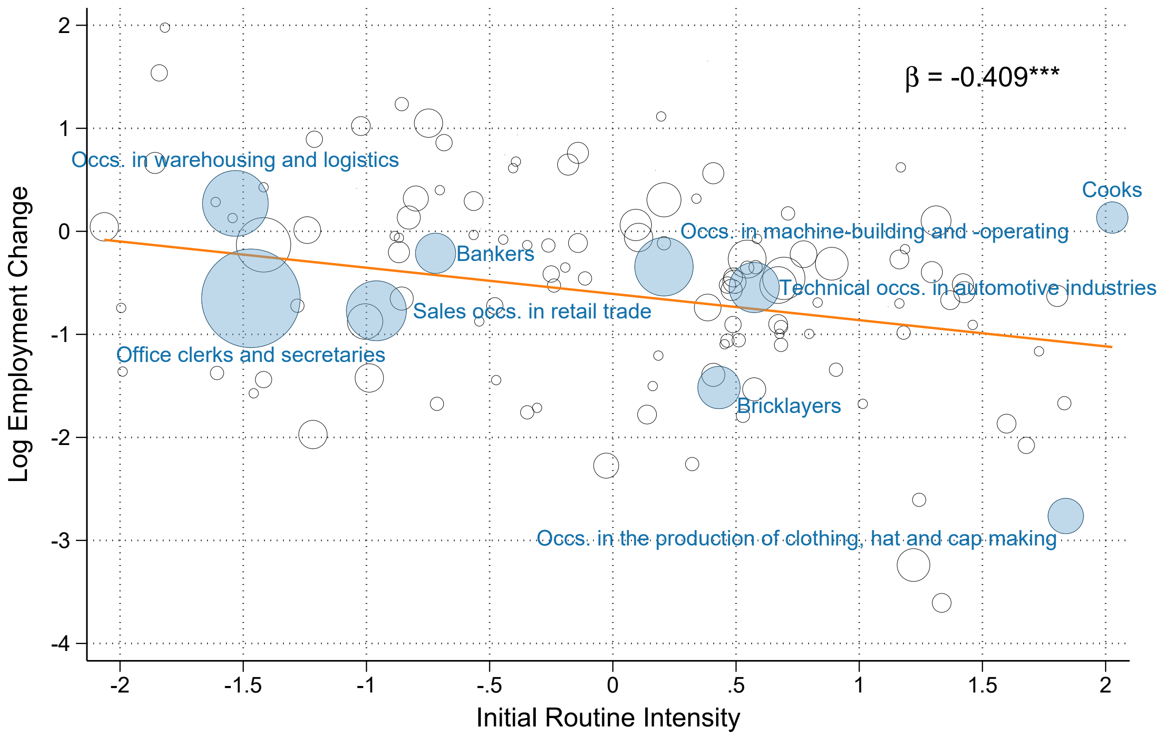


Figure presents a scatter plot of the relationship between occupational exposure to overall and digital patents for 1971–1996 (panel A) and 1997–2021 (panel B). Each point corresponds to the average percentile of overall ($x-$axis) and digital ($y-$axis) exposure of one occupational curriculum, where 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 A3: Employment Change by Initial Routine Task Intensity



Source: SIAB. Y-axis: Change in occupational regular full-time log employment between 1975 and 2017. The x-axis reflects standardized 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.

A.2 Curriculum change

Figure A4: Changes in Digital Technology and Social Skill Use in Updated Curricula by Production versus Service Occupations, 1976–2021

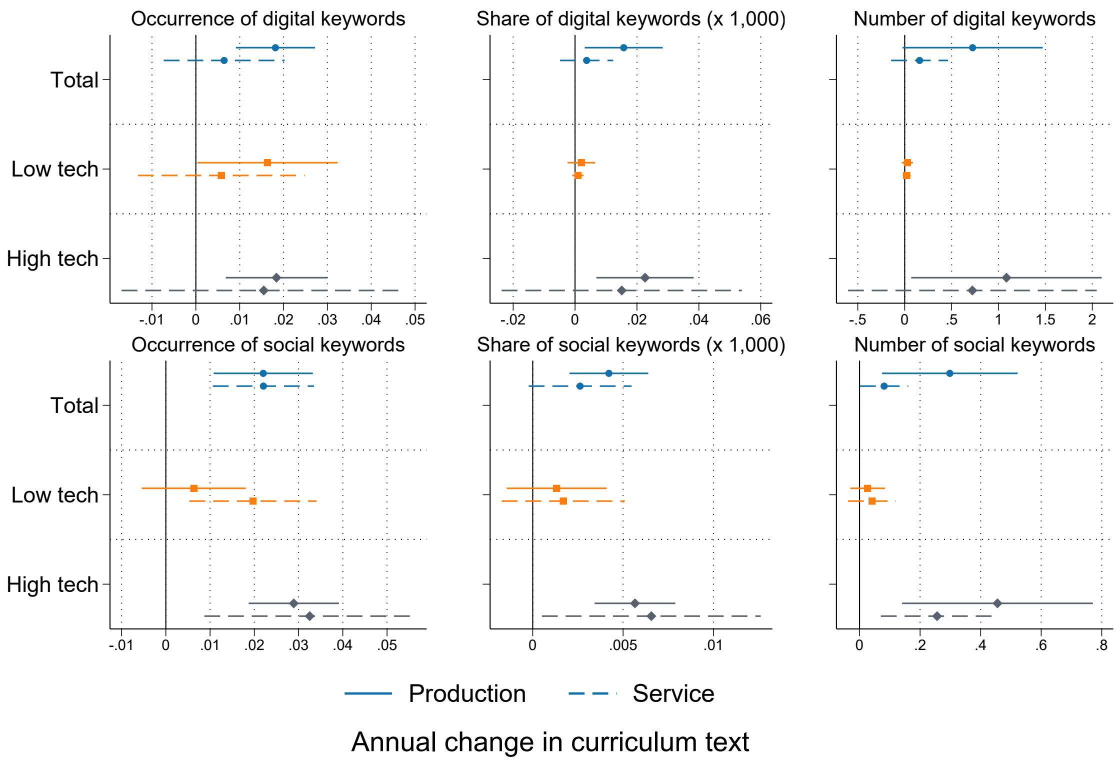


Figure reports coefficients on a linear timetrend, from a regression of keyword occurrence, keyword shares, or keyword counts in vocational training curricula (see equation (4)), for all curricula over 1976–2021. High tech (low tech) defined as curricula with an initial digital technology exposure above (at or below) the median across all occupations.

Figure A5: Changes in Digital Technology and Social Skill Use in All Curricula, 1976–2021

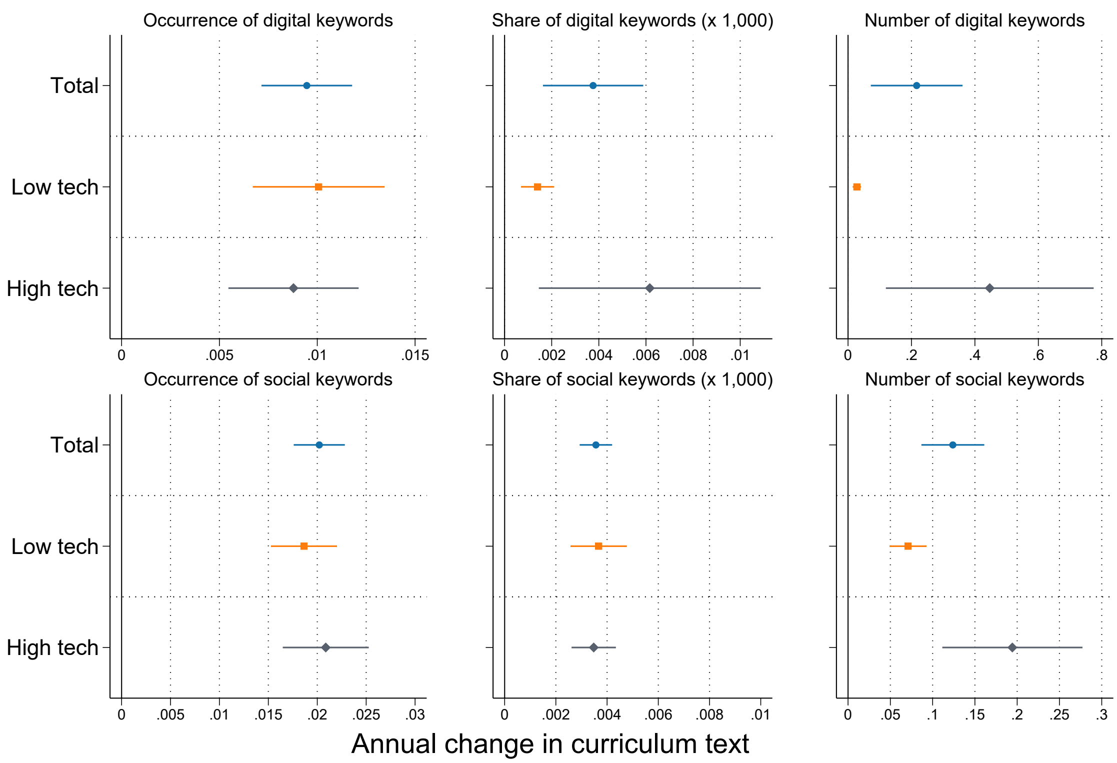


Figure reports coefficients on a linear timetrend, from a regression of keyword occurrence, keyword shares, or keyword counts in vocational training curricula (see equation (4)), for all curricula over 1976–2021. High tech (low tech) defined as curricula with an initial digital technology exposure above (at or below) the median across all occupations.

Figure A6: Changes in Routine Task Intensity in All Curricula, 1976–2021

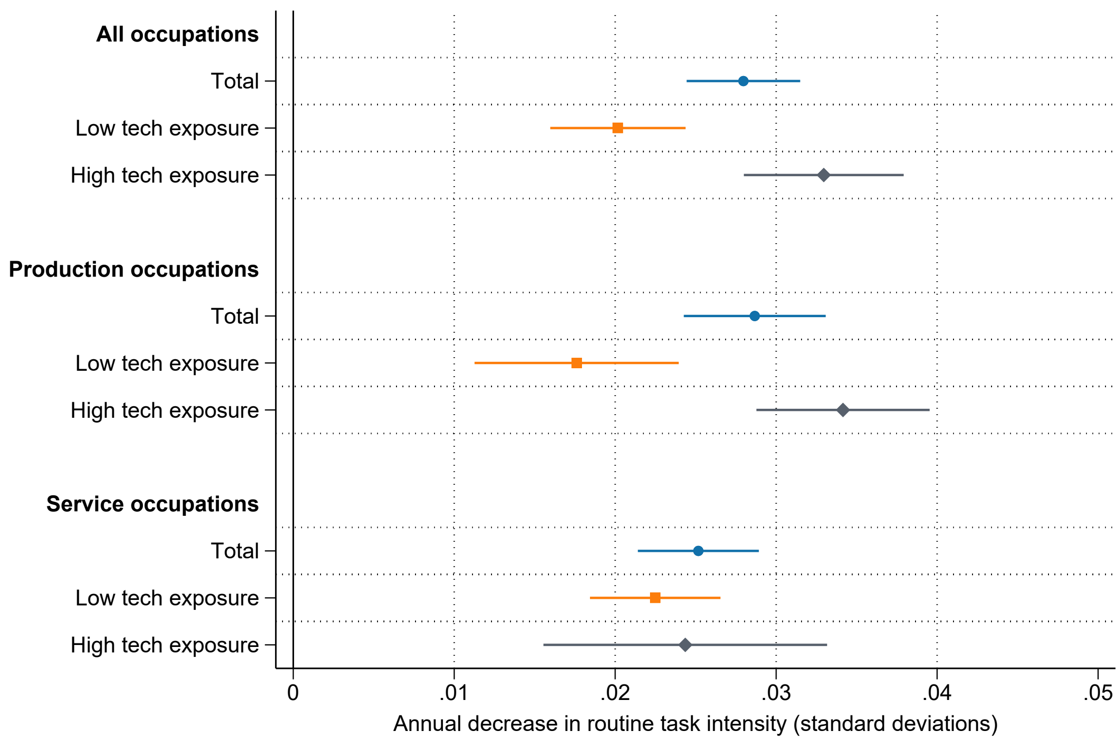


Figure reports coefficients on a linear timetrend, from a regression of routine task content in vocational training curricula (see equation (4)), for all curricula over 1976–2021. Horizontal lines reflect 95% confidence intervals. High tech (low tech) defined as curricula with an initial digital technology exposure above (at or below) the median across all occupations.

Figure A7: Changes in Word Complexity in Updated Curricula, 1976–2021

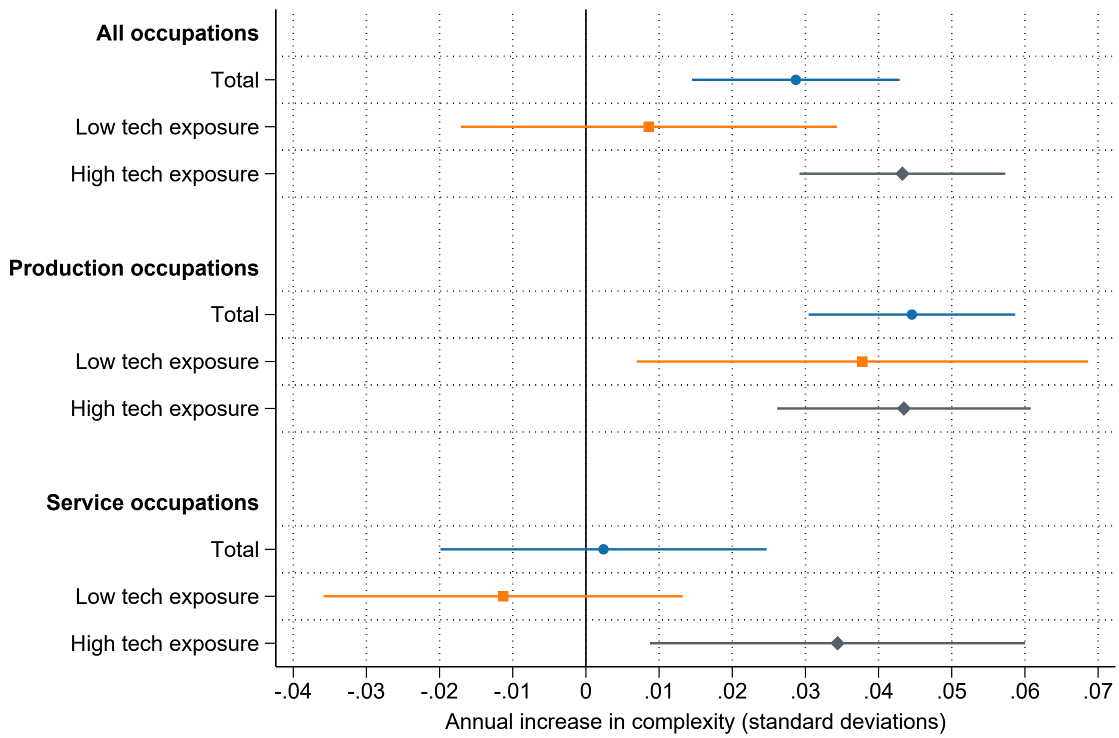
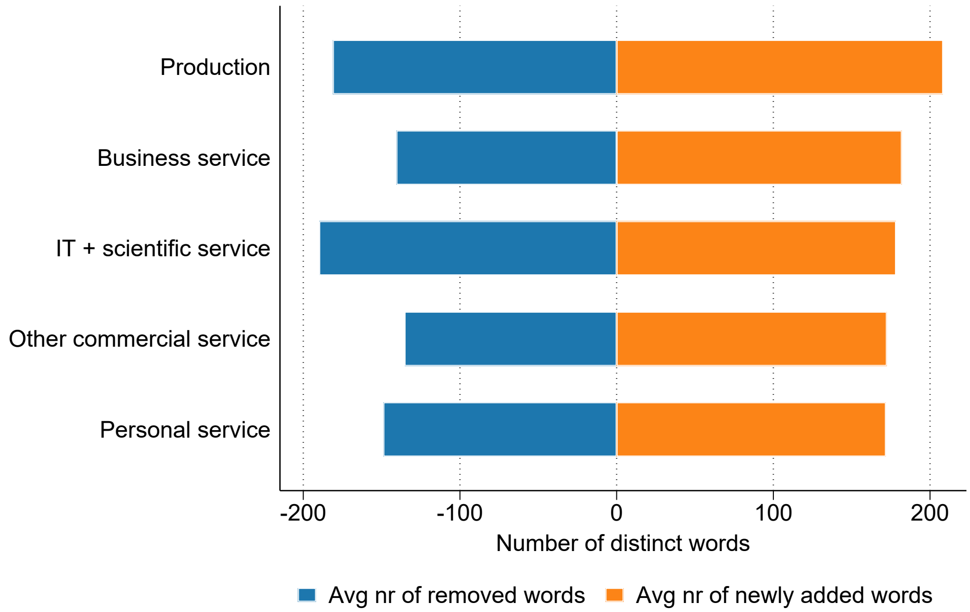


Figure reports coefficients on a linear timetrend, from a regression of complex word shares in vocational training curricula (see equation (4)), for all curricula over 1976–2021. Complex words are defined as those not in the Dale and Chall (1948) list, following Autor and Thompson (2025). High tech (low tech) defined as curricula with an initial digital technology exposure above (at or below) the median across all occupations.

Figure A8: Removed and Newly Added Words in Curriculum Updates

A. Number of Words



B. Number of Words a Share of Prior Curriculum Words

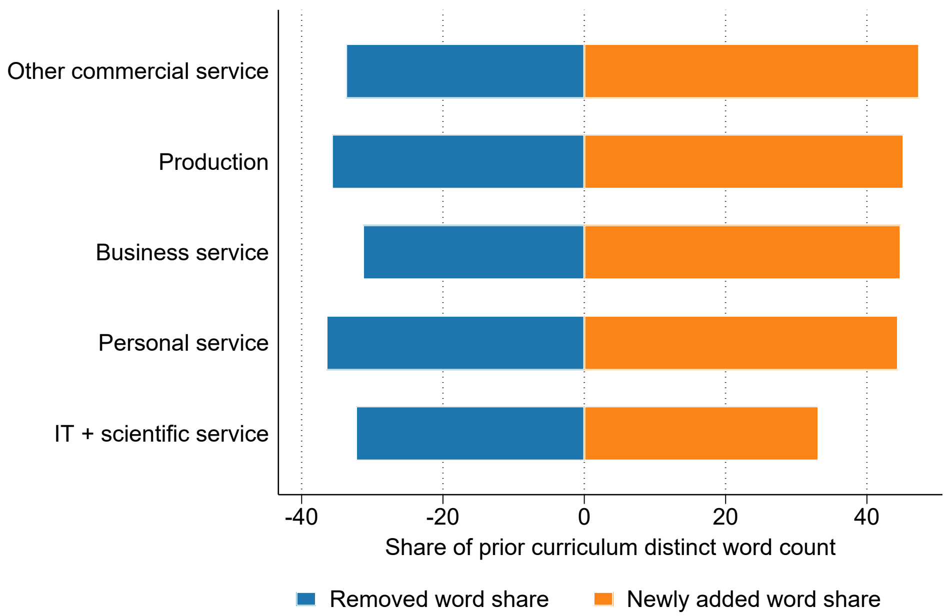


Figure presents the average number of distinct removed and distinct newly added words across curriculum updates in absolute number (panel A) and as a share of distinct prior curriculum word counts (panel B), by broad occupation.

Figure A9: 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.

Figure A10: Changes in Curriculum Complexity from Removed, Remaining, and Newly Added Words

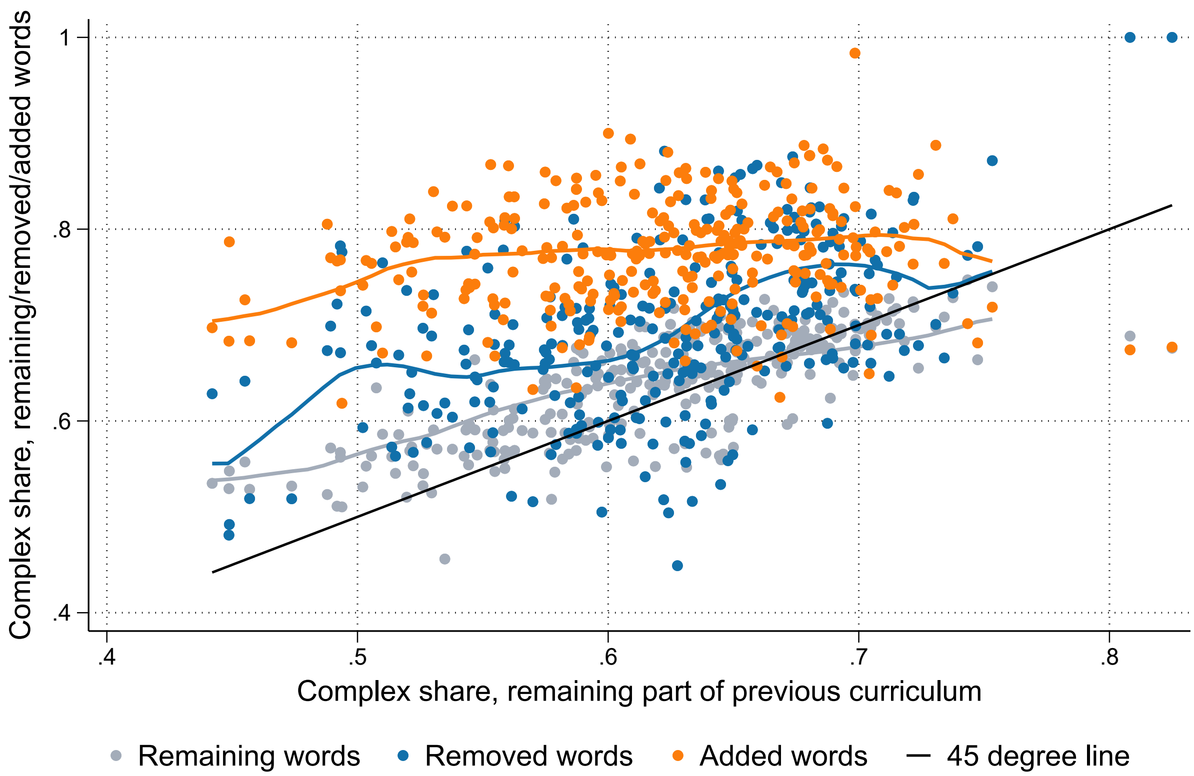


Figure presents the complexity of new curriculum words plotted against remaining words in the previous curriculum. Fitted lines are local polynomials weighted by training occupation employment shares.

A.3 Labor market impacts

Figure A11: Predicted Log Daily Wages for Treated and Control Group Workers

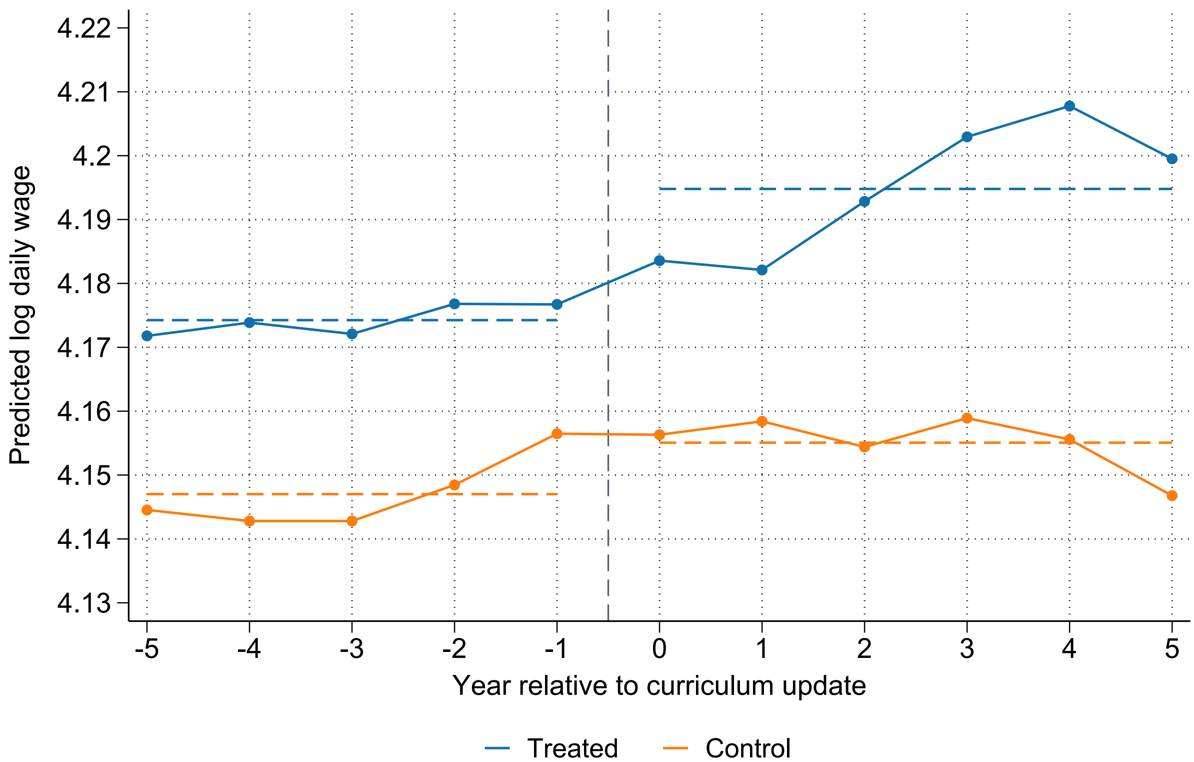


Figure reports predicted log wages for treated and control group workers using the stacked difference-in-differences estimate of equation (5). Log wages are predicted holding all covariates constant across events and between treated and control occupations. Level differences between treated and control occupations are recovered by calculating the difference in average occupation fixed effects and adjusting the predicted values by adding half of this difference to the treated group and subtracting half from the control group. Dashed lines indicate means of pre- and post-treatment predictions.

Figure A12: Impacts of Curriculum Updates on Training Firm Composition

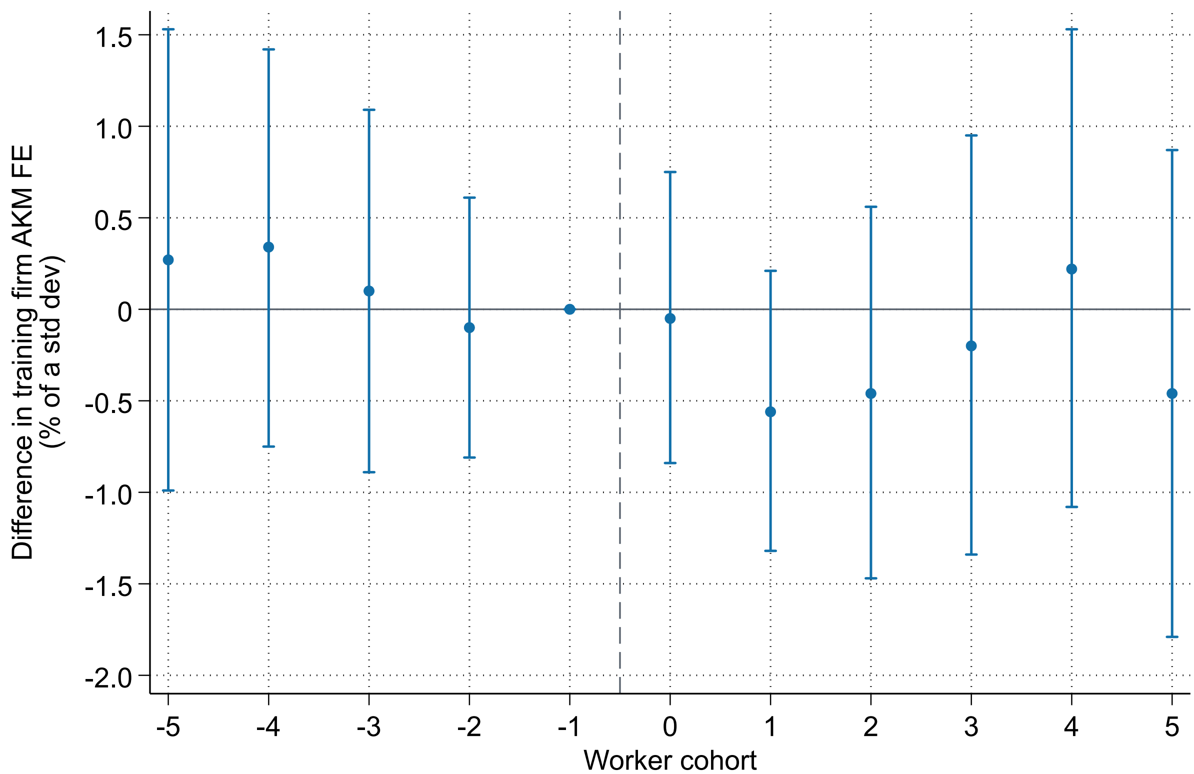


Figure reports stacked difference-in-differences estimates of equation (5), and 95% confidence intervals; estimated separately by year post training. Cohort 0 is the first cohort with the new curriculum; cohort -1 is the reference category. Standard errors clustered at the level of occupation by event. Based on 365 events, $N = 2,231,848$.

Figure A13: Impact of Curriculum Updates on Annual Income by Technology Exposure

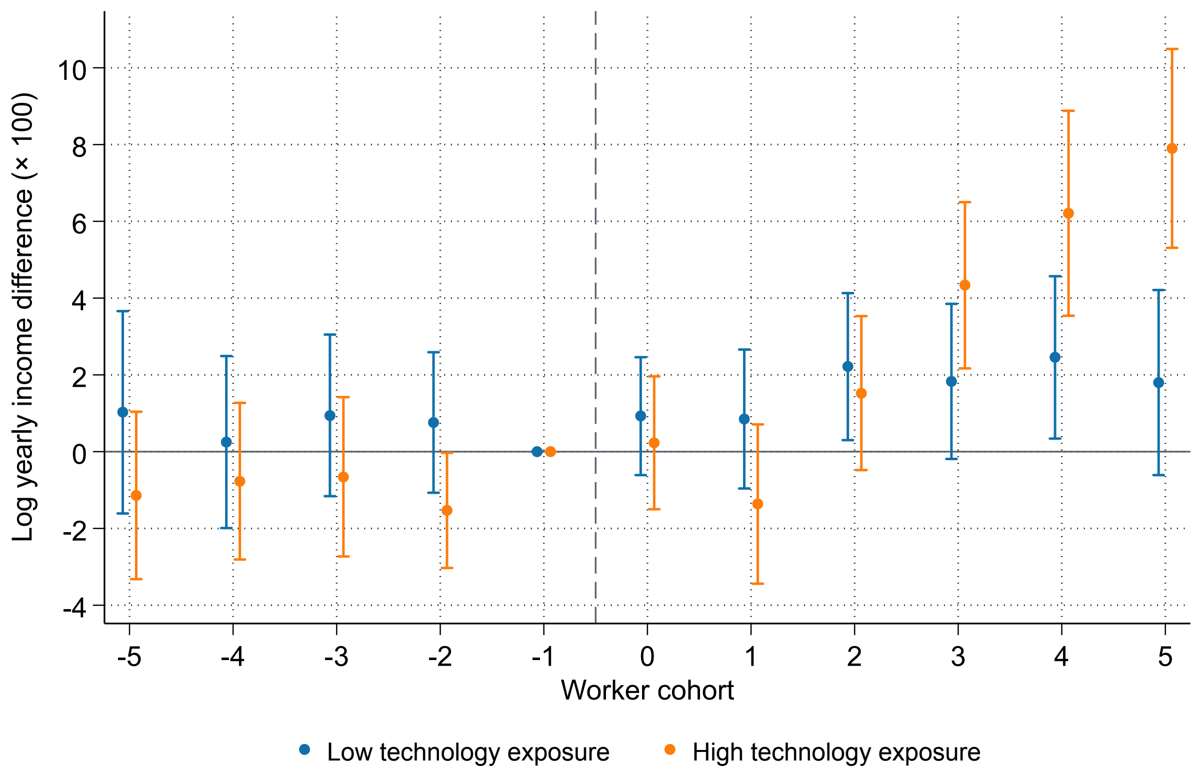
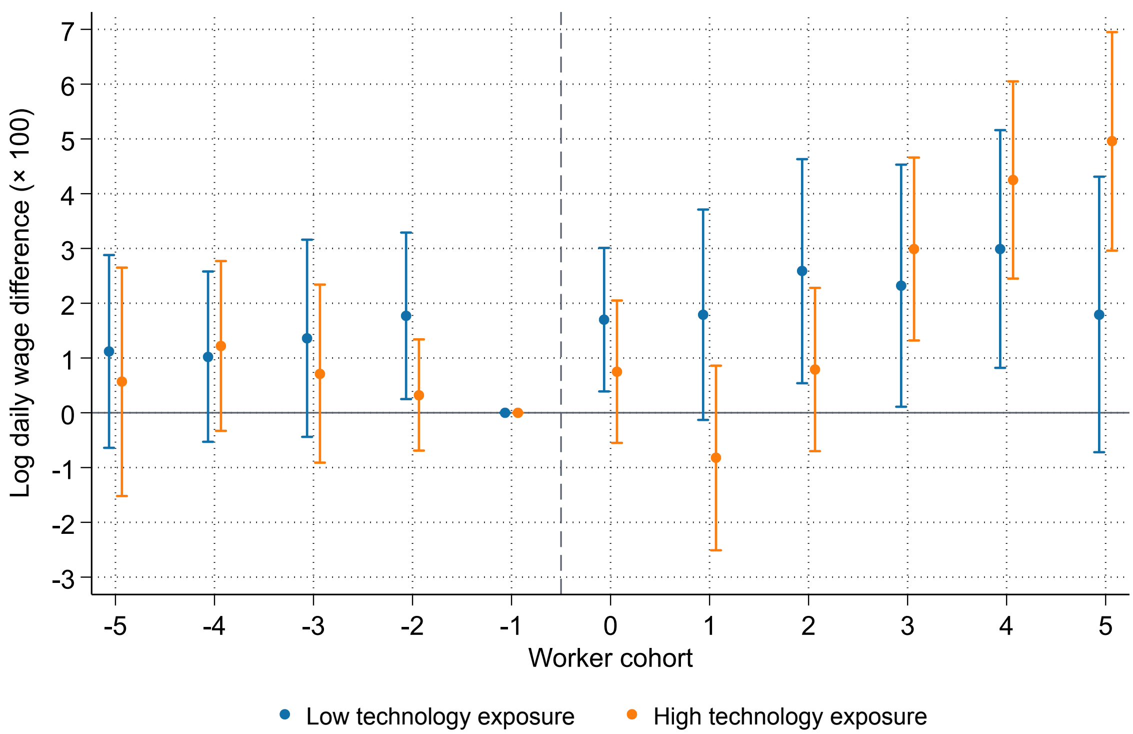


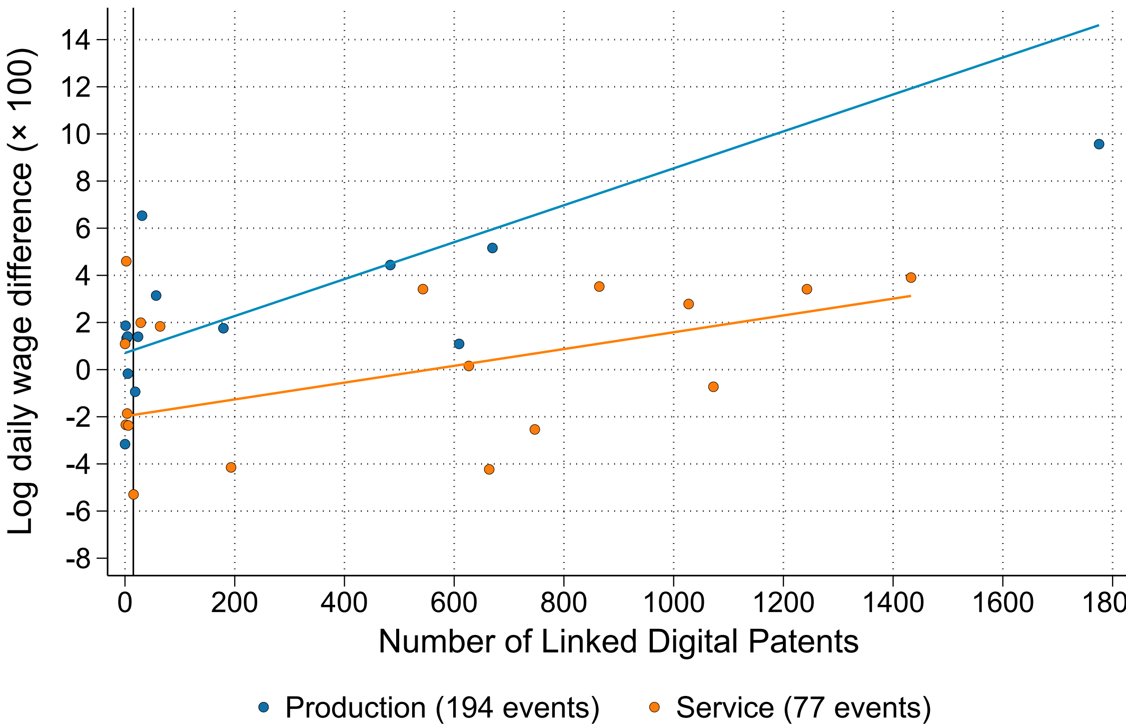
Figure reports stacked difference-in-differences estimates of equation (5), and 95% confidence intervals. Cohort 0 is the first cohort with the new curriculum; cohort -1 is the reference category. Individuals are included up to five years after graduation. Standard errors clustered at the level of occupation by event. $N = 4,251,785$ for high exposure (182 events), and $N = 4,690,903$ for low exposure (175 events).

Figure A14: Wage Impacts of Curriculum Updates by Technology Exposure, Controlling for Prior-Curriculum Technology Exposure



Stacked difference-in-differences estimates of equation (5), and 95% confidence intervals. Cohort 0 is the first cohort with the new curriculum; cohort -1 is the reference category. Individuals are included up to five years after graduation. Standard errors clustered at the level of occupation by event. Technology exposure of the prior curriculum is defined as the log number of (lagged) digital breakthrough patents linked to the occupation's curriculum in $t = -1$. $N = 3,611,583$ for low exposure (175 events), and $N = 3,430,761$ for high exposure (182 events).

Figure A15: Update-Specific Wage Impacts by Curriculum Technology Exposure



Binscatter of wage returns estimated separately for each curriculum update event, against curriculum technology exposure, measured as the count of linked patents. The vertical line indicates median technology exposure as used throughout the paper.

Figure A16: Log Daily Wage Impacts of Curriculum Updates By Post-Training Year and Technology Exposure

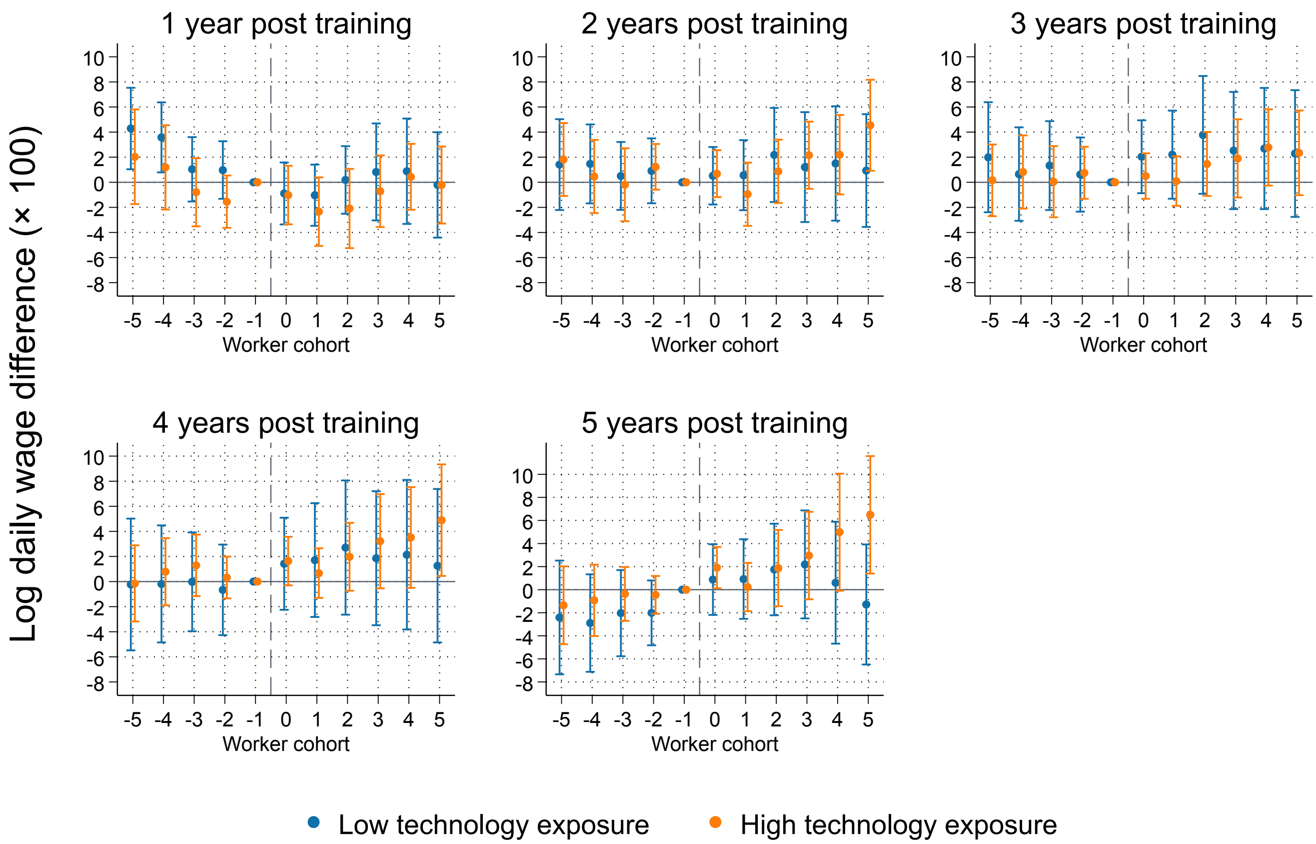


Figure reports stacked difference-in-differences estimates of equation (5), and 95% confidence intervals; estimated separately by year post training. Cohort 0 is the first cohort with the new curriculum; cohort -1 is the reference category. Standard errors clustered at the level of occupation by event. Observations numbers by year of post-training and technology exposure: $N_{1,high} = 792,314$, $N_{2,high} = 742,779$, $N_{3,high} = 729,085$, $N_{4,high} = 706,650$, $N_{5,high} = 688,608$; $N_{1,low} = 848,530$, $N_{2,low} = 804,461$, $N_{3,low} = 800,496$, $N_{4,low} = 789,952$, $N_{5,low} = 777,146$.

Figure A17: Log Daily Wage Impacts of Curriculum Updates, Controlling for Firm Fixed Effects

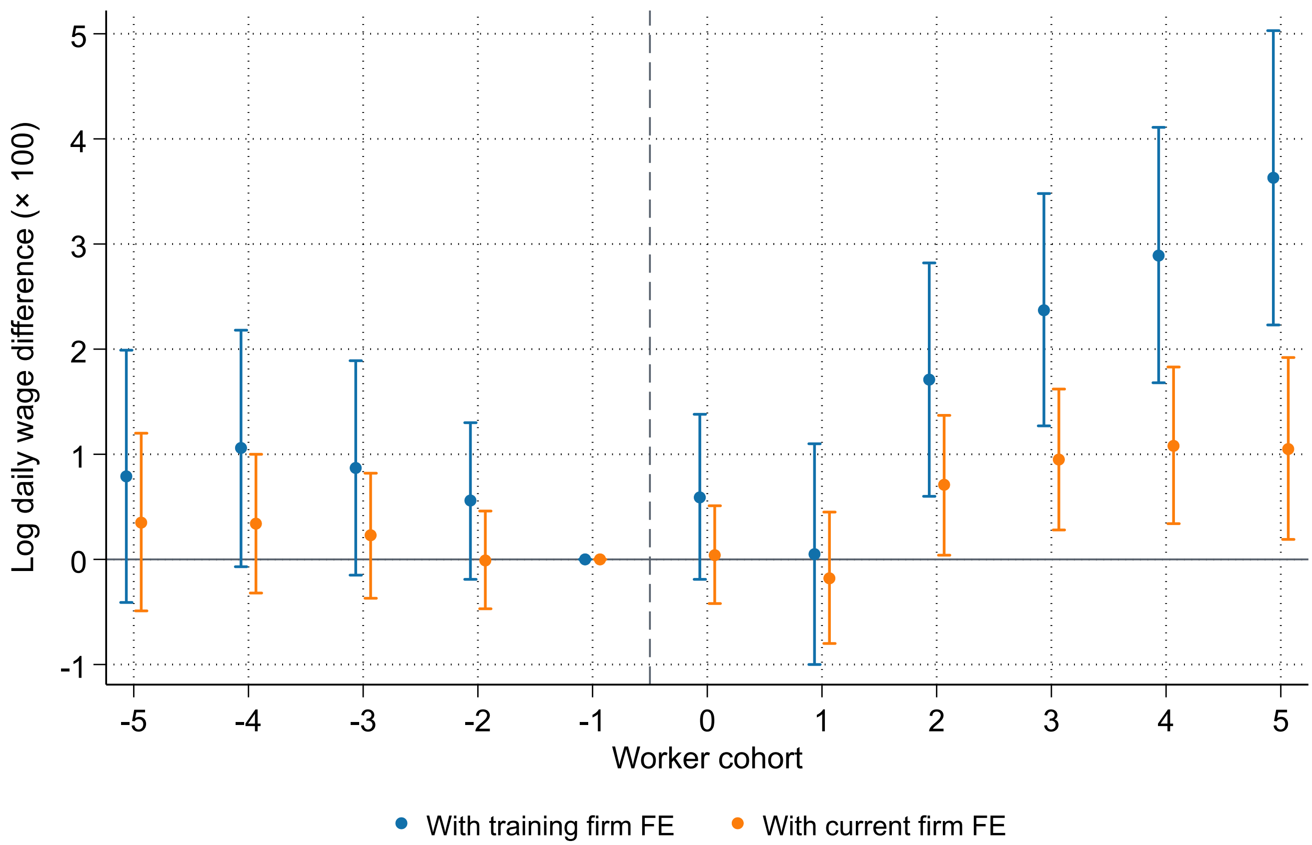
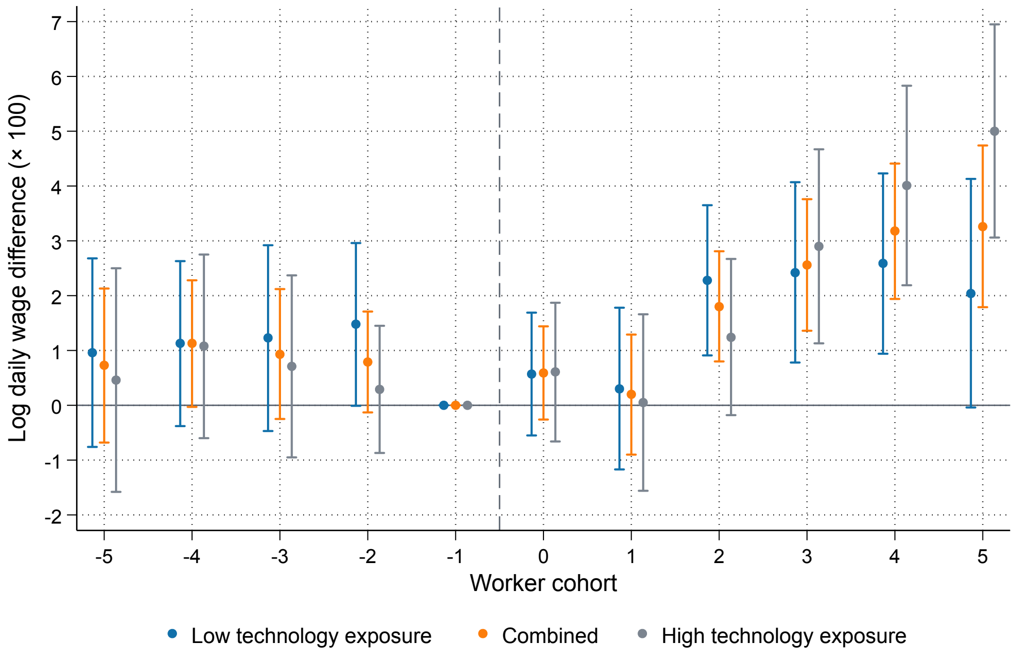


Figure reports stacked difference-in-differences estimates of equation (5), and 95% confidence intervals; estimated separately by year post training. Cohort 0 is the first cohort with the new curriculum; cohort -1 is the reference category. Standard errors clustered at the level of occupation by event. Model with training firm FE: $N = 7,715,849$; model with current firm FE: $N = 7,687,050$.

Figure A18: Impact of Curriculum Updates on Wages: Robustness Checks

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



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

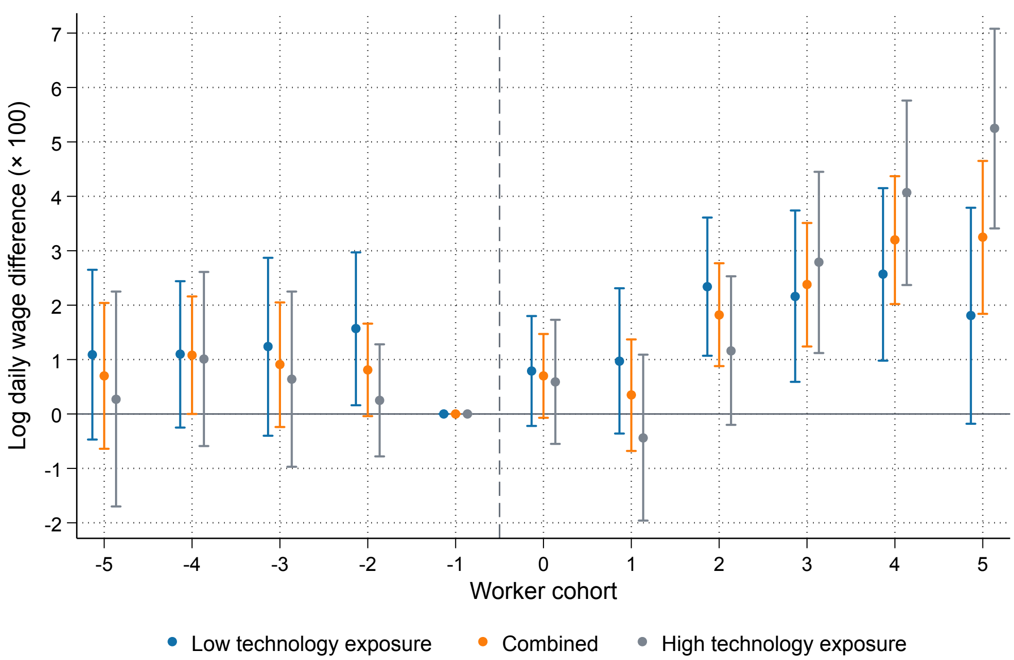
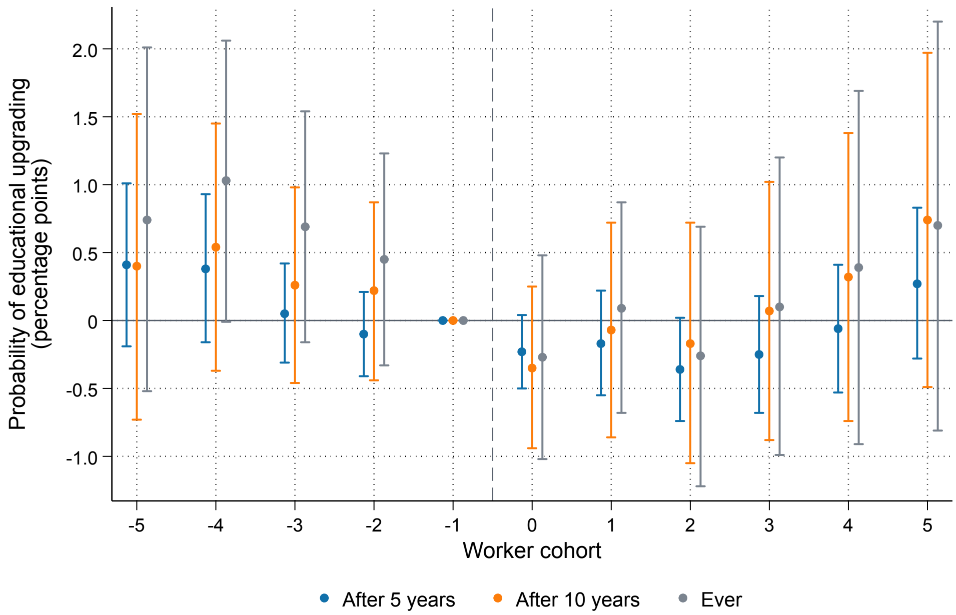


Figure reports stacked difference-in-differences estimates of equation (5), and 95% confidence intervals. Cohort 0 is the first cohort with the new curriculum; cohort -1 is the reference category. Individuals are included up to five years after graduation. Standard errors clustered at the level of occupation by event. Both panels based on 365 events. Panel A: $N = 4,833,972$ for overall; $N = 2,316,302$ for high exposure; and $N = 2,505,806$ for low exposure. Panel B: $N = 7,719,765$ for overall; $N = 3,670,190$ for high exposure; and $N = 4,029,336$ for low exposure.

Figure A19: Impacts of Curriculum Updates on Later Educational Upgrading

A. Obtaining a University Degree



B. Ever Obtaining Master Craftsman Degree

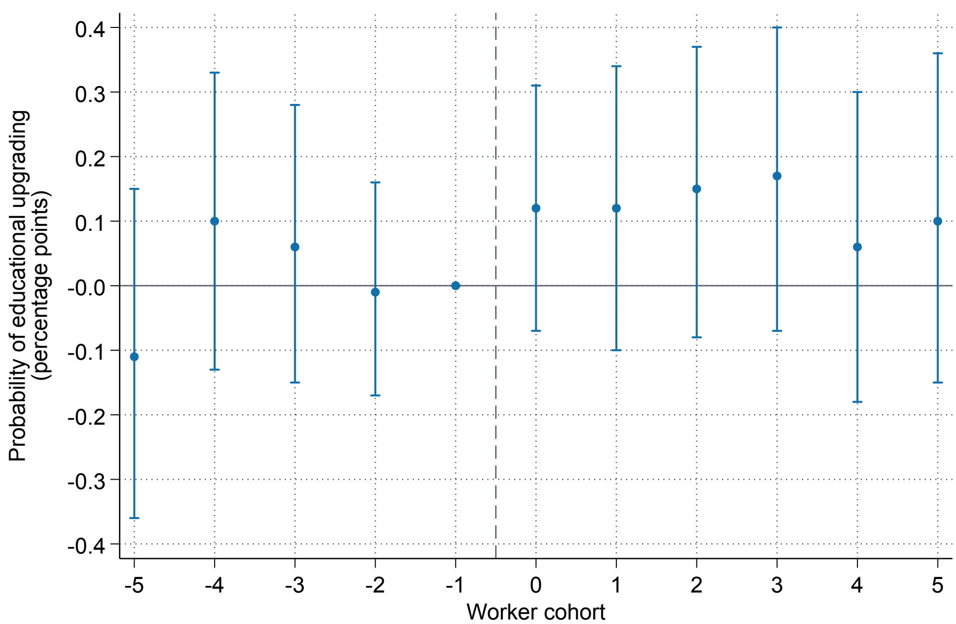
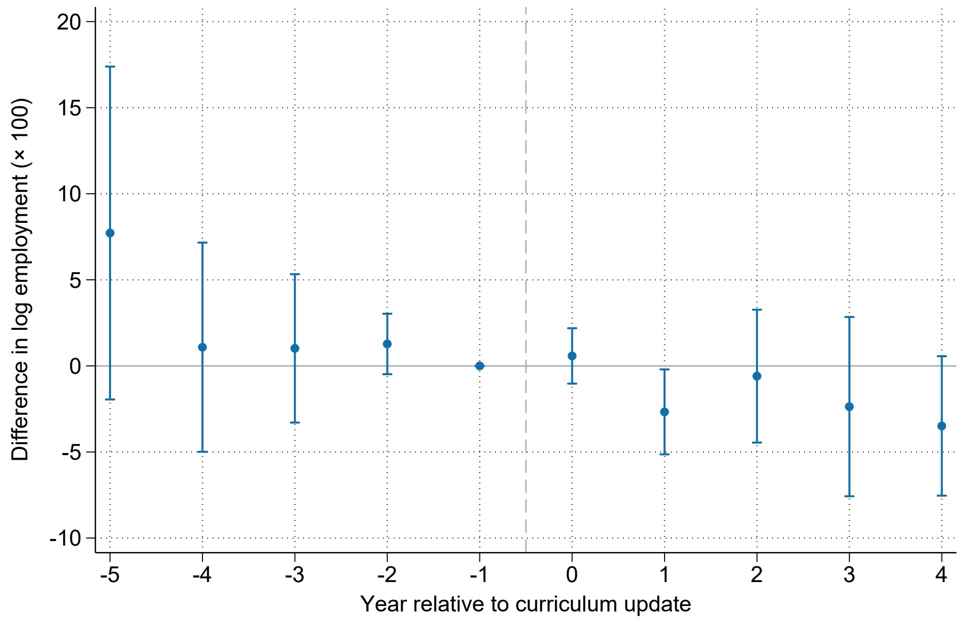


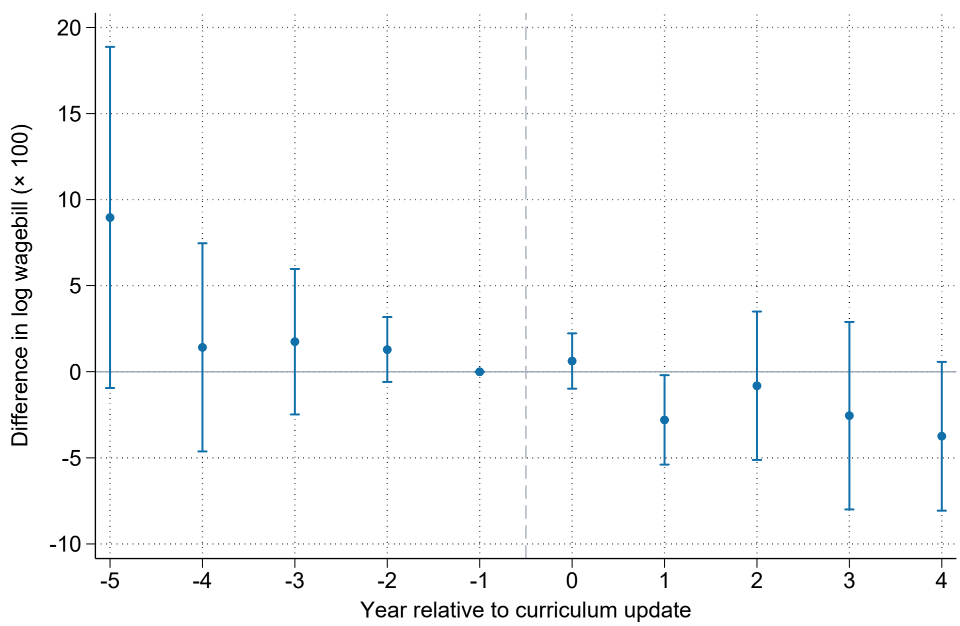
Figure reports stacked difference-in-differences estimates of equation (5), and 95% confidence intervals; estimated separately by year post training. Cohort 0 is the first cohort with the new curriculum; cohort -1 is the reference category. Standard errors clustered at the level of occupation by event. Based on 365 events for both panels. Panel A: $N = 2,231,848$; Panel B: $N = 2,231,848$.

Figure A20: 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.

B Appendix tables

B.1 Data and measurement

Table B1: Number of Tokens per Curriculum Section

	Mean	p10	Median	p90
Exam	3,896	1,448	2,381	5,748
Skills and Knowledge	16,302	2,882	5,435	18,416
Training Framework Curriculum	22,023	7,927	16,396	39,257
Total	34,374	14,719	24,059	54,179

Table B2: 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 B3: 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 B4: 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.

B.2 Curriculum change

Table B5: 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)	0.11	0.27	0.05	0.11	0.18	0.36
Number of digital keywords	3.99	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)	0.07	0.13	0.06	0.14	0.07	0.12
Number of social keywords	1.96	5.50	1.26	2.62	2.64	7.24

Table B6: 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	0.07	0.17	0.16	0.16	0.17	0.66	0.53	0.73
software*	0.19	0.25	0.16	0.38	0.57	0.28	1.38	1.42	1.35
computer*	0.14	0.12	0.14	0.15	0.09	0.17	0.40	0.23	0.48
ICT	0.19	0.18	0.20	0.26	0.34	0.22	0.84	0.87	0.82
online*	0.01	0.02	0.01	0.02	0.04	0.00	0.06	0.15	0.01
automat*	0.13	0.09	0.16	0.17	0.08	0.22	0.66	0.18	0.89
Social Skills Keywords									
team*	0.33	0.47	0.27	0.60	1.02	0.39	1.79	2.14	1.61
collaborat*	0.06	0.07	0.06	0.03	0.04	0.02	0.08	0.10	0.06
negotiat*	0.04	0.07	0.03	0.03	0.06	0.01	0.09	0.15	0.06

Table B7: 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 B8: 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 B9: 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 5 digit occupation. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table B10: 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, the reference group is always "no change". A training occupation may be split into several successors, each of which is an aggregation of multiple predecessors. The categories are therefore not mutually exclusive and the sum of the number of segregations, aggregations and pure content changes is larger than the number of changes. Linear probability models, weighted by employment size, coefficients multiplied by 100. Initial curriculum year fixed effects in five year bins. Standard errors clustered by 5 digit occupation. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table B11: 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 B12: Most and Least Routine-Intense Training Occupations

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

Routine intensity demeaned within years.

Table B13: Most and Least Routine-Intense Training Occupations

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

Routine intensity demeaned within years.

B.3 Labor market impacts

Table B14: Descriptives of Vocationally Trained Labor Market Entrants, Stacked Sample

	A. Treated			*B. Control*		
	Mean	SD	Median	Mean	SD	Median
Age	24.01	2.78	24.00	24.10	2.98	24.00
Year of birth	1978	9.00	1978	1978	9.00	1978
Female	0.31	0.46	0.00	0.52	0.50	1.00
Daily wage	76.66	30.53	77.98	72.76	30.39	73.40
Annual daily wage growth	0.38	10.41	0.05	0.31	4.65	0.06
Years of training	2.89	0.54	2.92	2.75	0.50	2.84
Typical years of training	3.12	0.41	3.00	2.86	0.34	3.00
Annual days employed	264	143	365	266	142	365
Annual labor earnings	20,606	14,999	22,212	19,667	14,413	20,877
Firm size	642	2,778	57	443	2,193	40
N unique workers		41,070			105,166	

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.

Table B15: Descriptives of Occupational Incumbents, Stacked Sample

	A. Treated		*B. Control*	
	Mean	SD	Mean	SD
Age	42.46	9.75	43.49	9.66
Year of birth	1959	11.00	1958	11.00
Female	0.23	0.42	0.26	0.44
Daily wage (euros)	112.91	48.43	116.79	51.68
Annual days employed	327	105	324	107
Annual labor earnings	39,615	19,289	40,761	20,583
Firm size	894	3,381	956	3,597
Job mobility (year-to-year):				
Occupation	0.05	0.23	0.04	0.21
Industry	0.06	0.24	0.05	0.22
Firm	0.10	0.30	0.09	0.29
N unique workers	673,555		548,250	

C 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 C1 highlights substantial curriculum change across a wide range of fields.

Figure C2 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 C1: U.S. Curriculum Change by Degree Field, 1990—2020

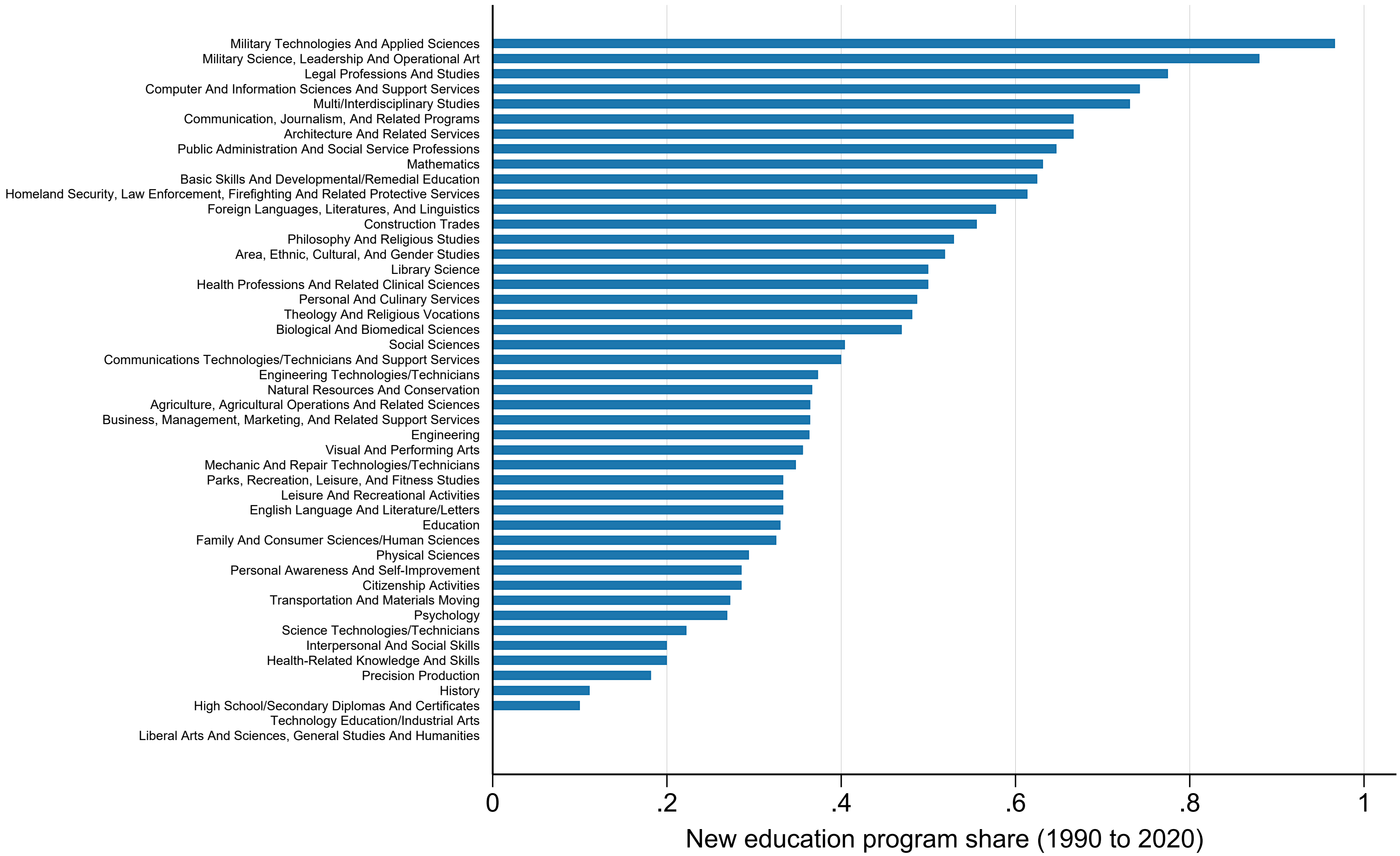


Figure plots the share of newly added degree programs by field based on CIP data.

Figure C2: U.S. Curriculum Change by Occupation, 1990—2020

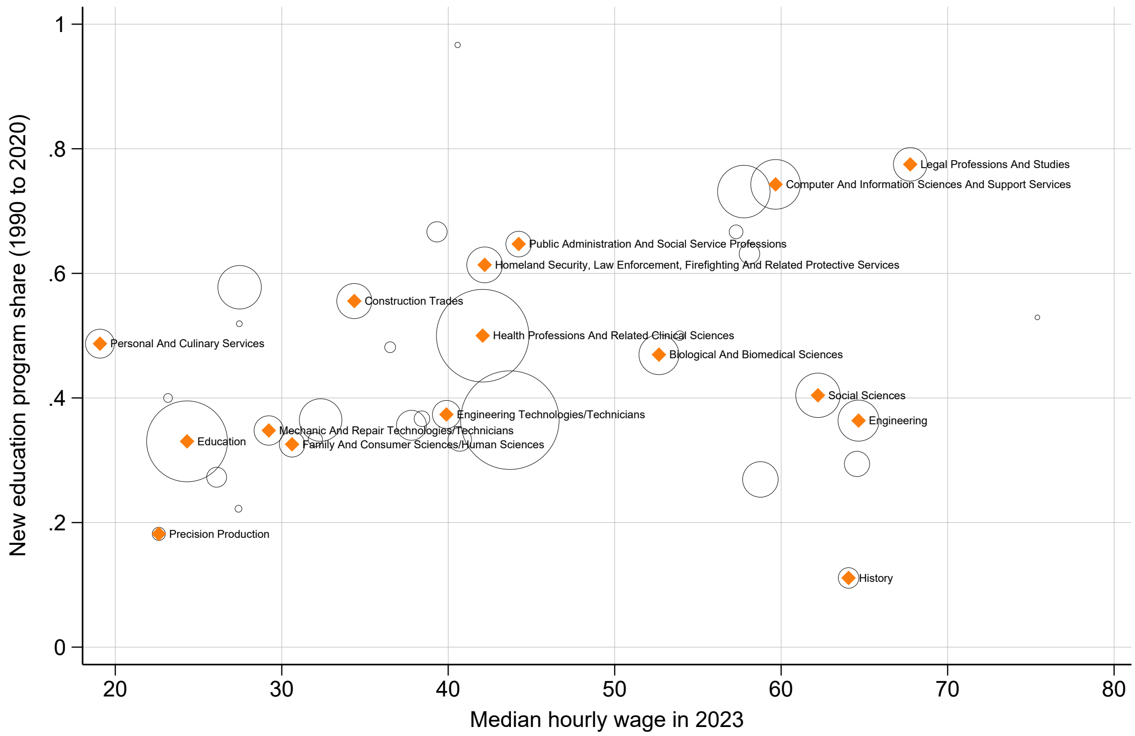


Figure plots the share of newly added degree programs by occupations ranked by median hourly wages, based on CIP data crosswalked to BLS data. The size of the circles reflects 2023 occupational employment shares.

D SIEED data construction details

We follow Dauth and Eppelsheimer (2020) in preparing the SIEED data. In particular, we derive several career indicators such as tenure, days in employment, etc. from the spell data; we merge the individual spell data with information on employers (location, industry, size) from the Establishment History Panel (BHP), we deflate wages using the consumer price index and we impute top-coded wages. Wages are top-coded in the data at the upper limit for social security contributions. Wages of trainees in the first years of graduation rarely exceed the contribution limit and thus are hardly ever censored or imputed. We retain the main employment spell of each individual in case of multiple concurrent spells, where the main employment spell is the one with the highest wage. The data provide daily information on workers' careers. We construct a yearly panel of workers by selecting workers' employment status at the 15th of October of each year. Most authors typically rely on the 30th of June (=mid of year). We use the 15th of October, because vocational training typically starts in August or September, so that by the 15th of October we are sure to cover all workers who started or completed vocational training in that year.

In addition to these standard steps from the literature, we derive further indicators from the data. In particular, we identify the start and end day of workers' vocational training, as well as training duration and occupation. We define the start of a workers' vocational training as the start day of an employment spell which is marked as a training spell, if there was no previous vocational training spell and if the workers has not had a completed vocational training before that spell (identified via the educational information). We identify the vocational training occupation of a worker by their occupation in that spell. We define the end of a vocational training of a worker by the end day of a vocational training spell that is followed by a non-training spell in combination with the worker having a completed vocational training status (identified via the educational information) in their next spell.

We drop Eastern Germany to avoid breaks in our data over time – East-German employment spells are available only from 1992 onward. We further drop workers who changed occupations during their training, as well as workers with unreasonably long or short training durations (less than 1.75 years, more than 4.25 years).

E Do curriculum updates impact 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 (application) numbers and trainee observables before and after curriculum updates in training programs which were updated versus those that were not.[39] The estimating equation is

$$Y_{jt} = \sum_{\tau} \beta_{\tau} \text{Update}_j \times I_{\tau} + \delta_j + \gamma_t + \varepsilon_{jt}, \tag{E1}$$

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 E1 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 E1 describes the apprenticeship positions: the number of training contracts, the share of these terminated before the end of training[40], 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 higher termination rate although these estimates are small and never statistically significant. Further, there is a very small increase in the pass rate for students enrolling in updated training

[39] 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.

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

programs, amounting to less than 2 percentage points (relative to a mean of 87%, shown in Table E1). We also do not observe changes in the share of unfilled apprenticeship positions (labeled 'excess supply of positions' in Figure E1) 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 E1 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[41]: 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 E2 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.[42]

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

[42]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 A20, 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.

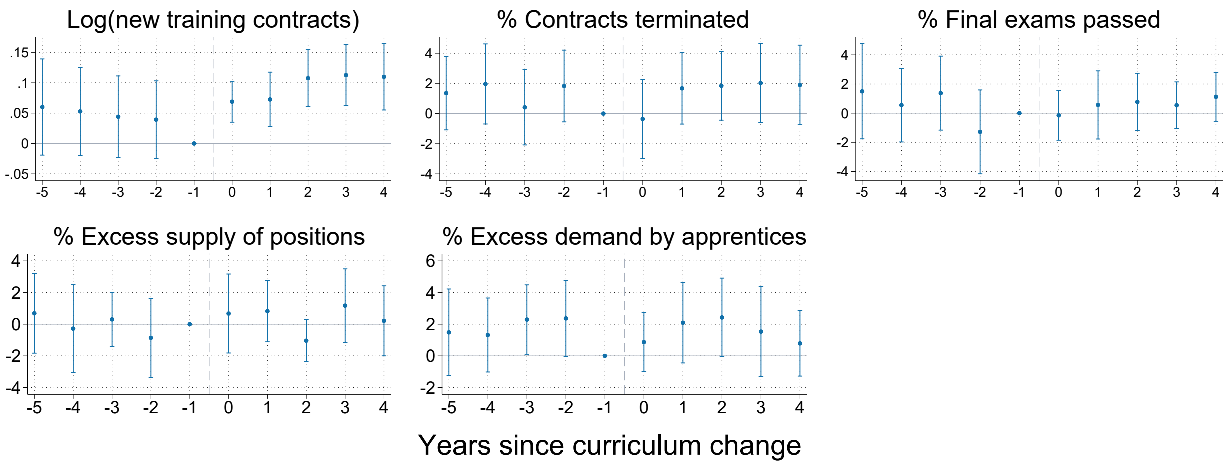
Table E1: Descriptives on Apprenticeship Positions and Trainee Composition

	Mean	SD	N
A. Apprenticeship positions, supply, and demand			
Log(new training contracts)	5.79	2.04	33,672
% Contracts terminated	20.62	13.85	32,706
% Final exams passed	89.37	7.9	7,466
% Excess supply of positions	4.19	5.19	7,869
% Excess demand by apprentices	10.86	11.12	7,869
B. Apprenticeship composition			
% Female	32.95	34.38	22,534
Average age in years	19.46	1.09	10,338
% Upper school track (1976–2006)	16.63	20.74	17,631
% Upper school track (2007–2022)	21.15	23.33	8,695
% Middle school track (1976–2006)	31.31	17.29	17,631
% Middle school track (2007–2022)	35.01	14.95	8,695
% Lower school track (1976–2006)	34.62	23.78	17,631
% Lower school track (2007–2022)	38.52	25.76	8,695
% No school (1976–2006)	1.95	3.34	17,631
% No school (2007–2022)	2.9	3.33	8,695

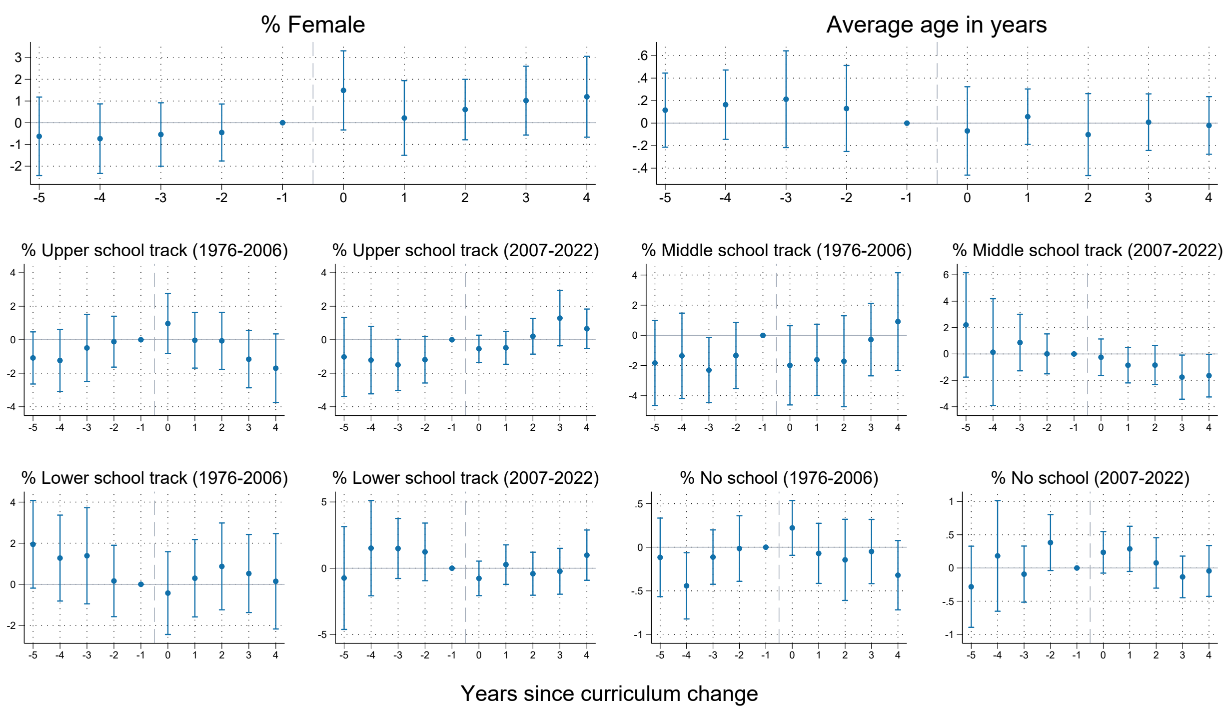
Mean and standard deviation in the initial year $\tau = -5$. N shows the number of observations included in the respective regressions: this varies across outcomes due to missing values.

Figure E1: Apprenticeship Positions and Trainee Composition Before and After Curriculum Updates

A. Apprenticeship positions



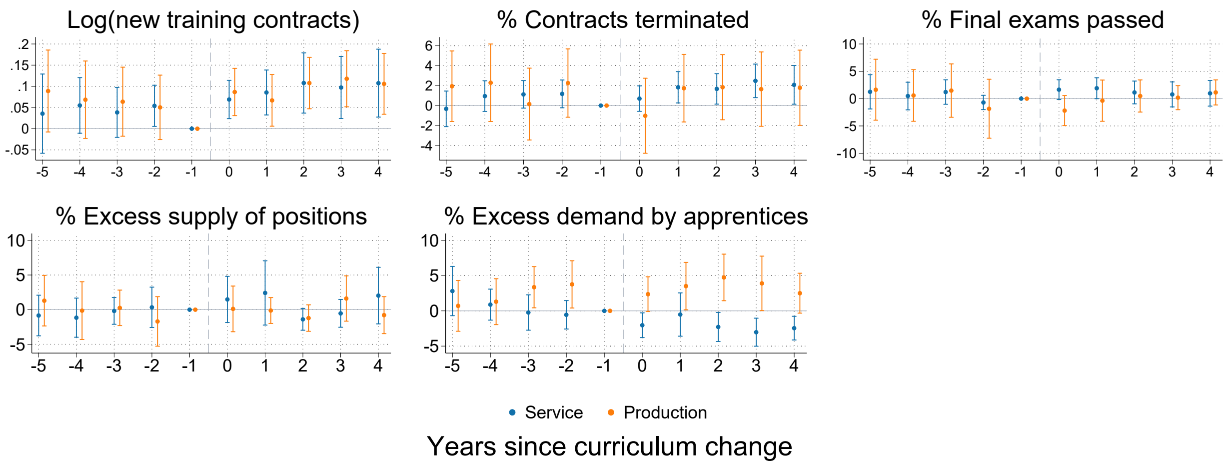
B. Trainee composition



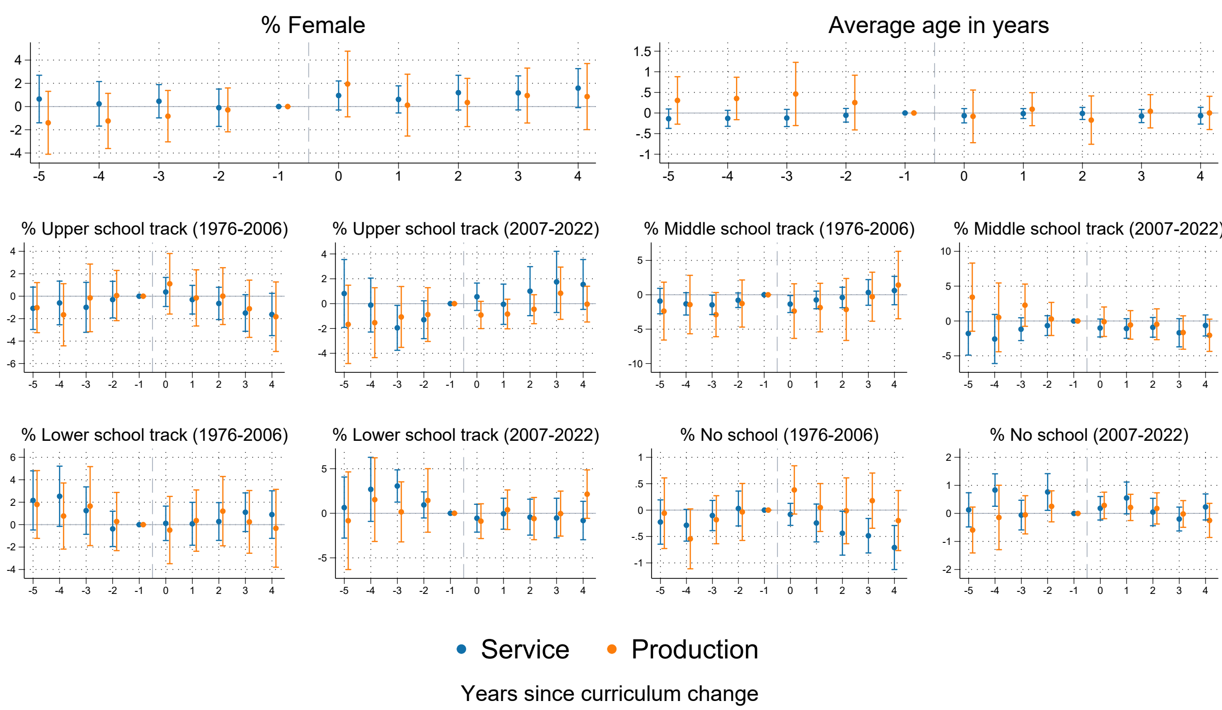
Stacked difference-in-differences estimates of curriculum updates on apprenticeship positions and trainee composition, comparing occupations with curriculum updates to occupations without updates. Based on 317 curriculum update events (pure content changes, aggregations without simultaneous segregations, and segregations without simultaneous aggregations) over 1976–2022, West Germany only, $N = 57,745$. The first year with the new curriculum is 0. 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 E2: Apprenticeship Number and Composition Before and After Curriculum Updates – Production versus Service Occupations

A. Apprenticeship positions



B. Trainee composition



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. Models specification in equation (E1). 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.