Expertise at Work: New Technologies, New Skills, and Worker Impacts*

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Abstract

Advancing technology changes skill demands: for human expertise to remain valuable in the labor market, skill supply must adjust. We study how new digital technology reshapes skill acquisition, and the resulting impacts on workers' careers. We construct a novel database of legally binding training curricula and updates therein spanning the near universe of vocational training in Germany over five decades, and link curriculum updates to breakthrough technologies using Natural Language Processing techniques. Our findings reveal that training adapts to technological advance by incorporating digital and social skills while reducing routine-intensive task content, mostly through new skill emergence. Using administrative employer-employee data, we show that curriculum updates help workers adapt to new skill demands, and earn higher wages compared to workers with outdated skills. By contrast, older occupational incumbents face declining wages, consistent with skill obsolescence. Firms respond by increasing capital investments when exposed to workers with updated skills. Our findings highlight the role of within-occupation skill adjustments in meeting evolving labor market demands for non-college educated workers.

Keywords: Technological Change, Skill Updating, Skill Obsolescence, Vocational Training, On-the-job training

JEL: J23, J24, J31

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1 Introduction

Advancing technology transforms the labor market by altering skill demands, thereby changing jobs' task content and wages. Both the automation of existing work and the generation of new labor-using tasks require workers to adapt. An expansive literature on the race between education and technology (Tinbergen, 1975) shows that the demand for skill has risen—particularly with the advent of digital technologies—and that rising educational attainment has been pivotal in adapting to increased skill demands over the past century, termed The Human Capital Century by Goldin and Katz (2008).

Much recent work on this race has focused on the demand side, providing a better understanding of which worker tasks have been automated, which have been complemented by advancing technology, and how specific technologies such as computers, robotics, or AI, affect labor demand.[1] By contrast, the recent literature is comparatively silent on the supply side of the canonical race, including on the content of human capital adjustments beyond years of schooling or (college) degree attainment (Deming, 2023). However, changing demands for *specific* skills, including social skills and IT skills (Deming, 2017; Deming and Kahn, 2018; Aghion et al., 2023), and transformed skill requirements *within* jobs (Spitz-Oener, 2006; Atalay et al., 2020) are quite distinct from increased educational requirements.

In this paper, we study how occupational skill supply adapts through changes in educational content, highlighting a potentially important mechanism by which the labor market responds to changing skill demands. Such educational adjustments may allow workers to work with new technologies relevant for their jobs, acquire complementary competences such as social skills, and forego training for tasks that are being automated. These adjustments suggest that technological advancements not only lead to worker skill obsolescence but also create new demands for expertise, enabling labor to enhance its value without necessitating additional years of education.

We leverage detailed curricula covering close to all vocational training in Germany over 1971–2021, linked with administrative labor market records, to answer three core questions. First, has advancing technology spurred updates in curriculum content over the past 50 years? Second, which specific skill changes are embodied in curriculum updates? And third, do skill updates impact workers' labor market outcomes, improving outcomes for labor

[1] For example, Acemoglu and Restrepo (2019); Acemoglu et al. (2020); Acemoglu and Restrepo (2022); Acemoglu et al. (2022); Webb (2020); Bessen et al. (2023); Hémous and Olsen (2022); Kogan et al. (2023); Autor et al. (2024); Bonfiglioli et al. (2024).

market entrants, reflecting augmented expertise; while inducing skill obsolescence among older occupational incumbents?

Vocational training in Germany is a full-time educational program following high-school, and is a particularly relevant setting to study the race between education and technology, for three reasons. First, the 1969 Vocational Training Act ensures that vocational training is codified in nationally standardized curricula that are regularly updated through an institutionalized process, discussed in more detail below. This institutional setting allows us to observe detailed educational content updates in a comprehensive and representative manner over half a century.

Second, as shown in Figure 1, vocationally trained workers are over-represented in the middle of the wage distribution, where many jobs have been strongly impacted by technology, and especially automation, over the past decades (Autor et al., 2006; Goos and Manning, 2007; Goos et al., 2014). Understanding how formal skill acquisition for these non-college educated workers adapts in response to technological change is a first-order question, especially as the labor market fortunes of non-college educated workers have generally deteriorated relative to their college-educated counterparts.

Third, a large share of the German workforce has obtained vocational training (around 65%, compared to 9% with a university degree).[2] These 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. By studying vocational training over 1971–2021, we therefore cover skill acquisition for a broad swath of the German labor market.

We employ two main empirical strategies to answer our research questions. First, to identify the effect of technological change on educational updates and content, we link vocational training curricula to lagged patents with Natural Language Processing (NLP) techniques, using a method pioneered by Seegmiller et al. (2023). To establish a causal connection, we use so-called breakthrough technologies (Kelly et al., 2021), as these 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 these curriculum updates. Second, to identify the causal effect of curriculum updates on individual worker outcomes, we use a stacked difference-in-differences (DiD) model leveraging curriculum update events. This approach compares cohorts of workers with old skills

[2] Averages over 1975–2017, based on the Sample of Integrated Labor Market Biographies (SIAB).

and cohorts of workers with new skills in an occupation that witnessed curriculum change to corresponding cohorts in occupations that did not witness curriculum change over the same time window. This identification strategy rests on the discontinuity of the change in skill supply, whereas potentially confounding factors such as changing skill demand plausibly evolve more smoothly over time. We also estimate DiD models exploiting curriculum updates for occupational incumbents to study skill obsolescence, and for firms to study impacts on capital investments.

We find that technological advances spur updates in vocational training: technology-exposed occupations are more likely to receive curriculum updates, and these updates also arrive more rapidly. A standard deviation increase in technology exposure raises the annual probability of curriculum updates by 1.2 percentage points, which is large compared to the average annual probability of curriculum updates of 3.8%. Moreover, curriculum content evolves toward less routine intensive tasks, and higher use of digital technology as well as social skills— especially among technology-exposed occupations—consistent with workers acquiring skills that are more complementary to advancing technology. Importantly, these changes are largely driven by the addition of new skills in training programs, rather than the removal of existing ones.

Using administrative employer-employee data, we show that educational updating helps labor market entrants adjust to changing skill demands, leading to higher earnings. The wage returns of curriculum updates are up to 3% over the first five years after training graduation, a sizable effect since we compare entrants trained for the same occupation but with an updated curriculum. Wage returns to curriculum updates are driven by technology-exposed occupations, suggesting that revised training content helps workers to keep pace with technological change— and these effects are not accounted for by changes in selection into updated training programs. Conversely, we find evidence of skill obsolescence among incumbent workers in occupations with skill updates, compared to incumbents in occupations without such updates. The wages of older occupational incumbents decline with entry of new-skilled workers, and younger incumbents are more likely to switch occupations and move to lower-paying firms. Reflecting the impact of technological change, firms increase capital investments when exposed to workers trained in updated curricula, particularly those with more technological content.

Our study contributes to several economic literatures. A first considers how technologies and institutions shape the long-run evolution of skill demands, occupational structure, and wage inequality (e.g., Goldin and Margo 1992; Katz and Murphy 1992; DiNardo et al.

1996; 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 creating new labor-using ones. We contribute by showing how skill acquisition in educational systems responds to technological advances, and the roles played by new skill emergence and skill obsolescence.

Second, we contribute to a literature studying within-occupational task change. This literature documents how tasks performed within occupations are transformed as a result of technology— and that such within-occupational shifts are at least as important as shifts in the occupational structure in accounting for the aggregate change in task demands (Spitz-Oener, 2006; Atack et al., 2019). Recently, this literature has advanced by identifying changes in skill demands along multidimensional measures of human capital, e.g. based on online job vacancies (Atalay et al., 2020; Deming and Noray, 2020; Acemoglu et al., 2022; Deming, 2023), and on measures of new tasks within occupations (Autor et al., 2024). While these papers focus on the demand side, we contribute by developing comparable multidimensional measures of human capital on the labor supply side, and by studying technological change as a specific driver of changes in within-occupational skill supply. We also document that these supply-side adjustments play an important role for workers' labor market outcomes.

Third, our work relates to a literature studying 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 the paper by Janssen and Mohrenweiser (2018), who pioneer a case study of a German vocational curriculum update for a single occupation in response to the adoption of Computerized Numerically Controlled (CNC) machinery. They show that this update deteriorated labor market outcomes for older incumbent workers in the occupation, indicating skill obsolescence. We contribute by considering close to all curriculum changes and all (patented) technology by linking vocational curricula to patents with Natural Language Processing techniques; by documenting how educational content has changed over the past five decades; and by identifying the causal effect of technological change on educational content. Compared to the broader skill obsolescence literature, our contributions are twofold. First, we identify specific educational updates and their skill content, and second, beyond studying skill obsolescence among (occupational) incumbents, we identify the gains to workers with up-to-date skills. The emergence of new, valuable expertise does not necessarily follow from skill obsolescence. Just as task displacement can occur without the creation of new tasks, incumbent workers' skills may become obsolete without corresponding benefits to new cohorts of workers, for example if the expertise of previous workers is now embodied in new technologies.

A fourth emerging literature studies changes in educational content, including how the composition of higher education programs responds to (local) labor demand (Conzelmann et al., 2023). Boustan et al. (2022) document that universities offer more CNC degrees following adoption of this technology. Biasi and Ma (2023) measure the distance between university curricula and the academic knowledge frontier, highlighting that students from schools with larger knowledge gaps have worse outcomes. A small subset of papers in this literature also specifically consider curriculum updates. Hermo et al. (2022) describe an increasing emphasis on reasoning as compared to knowledge in Swedish primary school curricula, and Light (2024) shows U.S. university degree content mostly adapts through newly created courses. We contribute by studying the effects of new technologies embedded in patents on curriculum content over five decades, and by identifying the causal impacts of these updates on worker outcomes.

Our paper also relates to a broader literature analyzing the content of vocational training systems (Eggenberger et al., 2017, 2018; Rupietta and Backes-Gellner, 2019; Kiener et al., 2022, 2023; Langer and Wiederhold, 2023; Cnossen et al., 2023; Schultheiss and Backes-Gellner, 2024; Buehler et al., 2025). This literature documents and categorizes skills contained in these curricula, and their (changing) returns in the labor market. Our paper contributes by considering curriculum updates, how these relate to advancing technology, and their causal impact on worker outcomes.

The remainder of this paper is structured as follows. The next section outlines 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 updates in vocational training content for individual workers, and Section 5 studies impacts on firm investments. Section 6 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 are administrative data on firms and their workers, which we describe in Section 4 when we turn to the labor market impacts of curriculum updates.

2.1 Training occupations and training curricula

In Germany, vocational training typically combines classroom schooling (1–2 days a week) with on-the-job training at a firm (3–4 days a week), 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. Both the final written and practical exam are not conducted by the training company itself, but by an external board of examiners, which consists in equal parts of representatives from employer associations, employee associations, and vocational school teachers. 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 by means of a well-defined and institutionalized process.[3] Updates of training curricula are initiated either by the employers (through individual firms, employer associations, or professional organizations, so-called *'Kammern'*), the employees (through labor unions), or the Federal Institute for Vocational Education and Training (*Bundesinstitut für Berufsbildung*, BIBB).[4] Typically, it takes around one year after an update has been suggested by one of these partners to be agreed upon (Bundesinstitut für Berufsbildung, 2023), and another six months for it to be reflected in law. This implies that curriculum updates arrive around 1.5 years after the update was first initiated. For some updates, firms are granted a grace period before they must comply with the new curriculum, while the majority of curricula take effect at the start of the next training year.[5] While this specific institutional setting allows us to observe curriculum updates in a comprehensive way over 50 years, changes in educational content are common in other settings as well: in Appendix C we use U.S. Clas-

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

sification of Instructional Programs (CIP) data to document widespread emergence of new degree programs over the past three decades.

Our analysis focuses on occupations where a vocational training curriculum is observed ('training occupations').[6] We build a training occupation by year panel over 1971–2021 which contains training occupations with their occupation classification code and an indicator of the occurrence of a curriculum change. The panel is unbalanced as training occupations only enter the panel once the first curriculum is observed post 1969 and need not exist over the entire time interval.

To obtain training curricula and their changes, we proceed in three steps. First, we collect the curricula of the vocational training programs 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, spread over 11.1 pages on average. We machine-translate curricula from German to English.[9]

Second, we match these curricula to a separate database containing entries for all curricula changes ('Index of Recognized Training Occupations', or *Verzeichnis der Anerkannten Ausbildungsberufe*) based on the training occupation title and the year of issue. This allows us to link preceding training occupations to current and future training occupations in cases where the occupational title 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.

[6] While not all workers employed in these occupations hold a vocational training diploma, on average 78% do. Averages over 1975–2017, based on the Sample of Integrated Labor Market Biographies (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.

Third, we match the training occupation title to official occupation codes from the 2010 German classification system (*Klassifikation der Berufe*, KldB) at the 5-digit level based on a crosswalk provided by the BIBB (Lohmüller, 2021).[10] The 492 training occupations can be linked to 237 distinct KldB occupations (henceforth: occupations).[11]

We derive different indicators from the curriculum changes at the training occupation by year level for empirical analyses. 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 (i.e. merging of existing occupational training programs into fewer training programs); and updates in curriculum content accompanied by the segregation of a training occupation (i.e. splitting up of an occupational training program into several training programs).[12] We additionally characterize the skill content of the curriculum change by analyzing changes in textual descriptions, as described in Section 3.2.

To contextualize these jobs in the broader German labor market, Figure 2 shows separate boxplots of wages for training occupations and for all other occupations. The median real training occupational wage is around 99 euros daily, slightly below the 109 euros observed in other jobs. While daily wages in training occupations vary meaningfully, with an interquartile range between 83 to 107 euros; the interquartile range for other jobs is significantly wider, between 93 and 167 euros. This highlights that training occupations are middle- to low-

[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 clustering or fixed effects. 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 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 pure content updates, and those accompanied by renamings, aggregations, or segregations is larger than the total number of changes.

paid jobs compared to other occupations in the German economy. It is worth noting that collective bargaining coverage in Germany is around 40%, not particularly high compared to some other European countries like France or Italy, where it is closer to universal (Jäger et al., 2025).

Table 1 lists the ten largest occupations with a training curriculum in our sample, based on employment counts. This includes Office clerks and secretaries, which have 11.2% share in total employment on average over the period; Occupations in warehousing and logistics; Occupations in machine-building and -operating; Retail sales occupations; Professional drivers (cargo trucks); and Technical occupations in automotive industries, each of which has 3 to 4% shares in total employment. While daily real wages vary between 152 euros for Occupations in electrical engineering and 70 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 1975–2017), 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 3 through 6 show machine-translated excerpts of training curricula for two occupations, Process control electronics technicians (from the 1992 curriculum and its 2003 updated version) and Industrial clerks (from the 1978 curriculum and its 2002 updated version). These examples highlight both the specificity of these curricula and substantive changes over time.

Figure 3 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 4 shows excerpts illustrating changes in the 2003 update. Apprentices in the same training occupation (now named Electronics technician for automation technology) must learn to install and configure IT systems and advise and support customers. The former is further detailed as, among other things, "selecting hardware and software components", "installing and configuring operating systems and applications", and "integrating IT systems into networks". Further, "solving problems in a team" is now mentioned among operational and technical communication skills.

The training for Industrial clerks similarly shows important changes in its 2002 curriculum (Figure 6) relative to its 1978 incarnation (Figure 5). 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. 3.8% of the 11,843 training occupation-year observations have experienced a curriculum update over the past five decades, with the majority only involving a content update ($0.021/0.038 \times 100 = 55\%$). 40% ($= 0.015/0.038 \times 100$) 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 7% of all curriculum updates.

Figure 7 shows the total number of curriculum updates over time, i.e. the number of new curricula conditional on observing the training occupations' 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). This increase in curriculum change in part reflects the rising number of observed preceding curricula, as seen in Figure 8. In our analyses, we will not exploit this time series variation because it may also capture changing time investments in curriculum updating for political or administrative reasons: instead, we leverage the distribution of changes across training occupations within a given year.

Table 3 shows the most and least changed 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 which are updated at some point, the least frequently updated ones include Gardeners, Foundation engineering specialists, Asphalt builders, Civil engineers, and Industrial insulators. There are also several occupations which have seen no changes to their training curricula over our time window: this includes Brass instrument makers, Delivery drivers, Floor layers, Glass blowers, Hotel clerks, Makeup artists, and Stage painters and sculptors.

The two panels of Figure 9 show the distribution of curriculum updates more broadly, for initial training occupation observations. Panel A plots the distribution of years until a curriculum is changed, highlighting that this varies widely across curricula: some are updated within years with others changed only after two or more decades. On average, a curriculum is updated after 15.3 years, as seen from the bottom row of Table 2. The distribution of curriculum change varies substantially across broad occupation groups, shown in panel B of Figure 9: the curricula for IT and scientific service occupations are updated with the highest regularity, followed by Business service occupations, Production occupations, and Other commercial service occupations. Personal service occupations 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, despite not capturing all innovations, such as those less suited to protection as intellectual property.

Rather than using all U.S. utility patents, we use the subset which Kelly et al. (2021) classify as technological breakthroughs.[13] These breakthroughs are both novel (i.e. distinct from previous patents) and influential for subsequent innovation (i.e. similar to later patents), empirically operationalized as the top 10% of patents by year in terms of forward-to-backward textual similarity. Further, we lag breakthroughs by 20–25 years relative to our 1971–2021 curriculum data, implying we consider technological breakthroughs occurring over 1946–2001.

Using lagged breakthroughs as opposed to all patents serves two purposes. First, breakthroughs are the most transformative technologies (Kelly et al., 2021), and therefore likely to be important for workers. This should result in more 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 also 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

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

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 empirical evidence). Further, lagging breakthroughs by twenty years allows for a delay between patenting of these novel technologies and subsequent follow-on innovation as well as implementation in the workplace—below, we explore the lag structure using local projections (Jordà, 2005).

Figure 10 shows the distribution of breakthrough patents across eleven broad technology classes as defined by Kelly et al. (2021) over time. We use breakthroughs over the 1946–2001 period, which has seen the largest expansion of breakthrough patenting in the technology class "Instruments & Information", capturing digital technologies. Towards the end of the period, these technologies comprise the majority of patenting, reflecting the Digital Revolution.[14] In our baseline models we focus on digital technologies, though we show robustness using breakthrough patenting activity across all technology classes.

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 as well as patents.[15] We follow Seegmiller et al. (2023)'s linking method and first retain verbs and nouns excluding standard stopwords plus a small number of source-specific stopwords to compute Term-Frequency Inverse-Document-Frequency (TD-IDF) weighted averages of pre-trained word embedding vectors provided by Pennington et al. (2014). We then obtain the cosine similarity between every patent-curriculum pair, and normalize these similarity scores by subtracting the median similarity for each patent (as in Autor et al. 2024) to avoid assigning low similarities to patents using more technical language. Appendix Table 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

[14] 2.1% of U.S. digital breakthrough patents since 1976 are held by German inventors.

[15] 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.

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.

Training occupations are very differently exposed to technological change embedded in patents, as illustrated by the distribution of the number of linked digital breakthrough patents across occupations in panel A of Figure 11. We will exploit 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 A1 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, plant mechanics, and tool mechanics, and cutting machine operators. Jobs with a 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, among business service occupations, Media designers are the most exposed while Personnel services clerks are the least exposed.

3 Does technology exposure spur curriculum change?

This section empirically assesses whether exposure to technology spurs curriculum change, by considering (1) curriculum updates, and (2) the skill content of these updates. We take up the effects of curriculum updates on labor market outcomes in Section 4.

3.1 Curriculum updates

We start by considering the panel of training occupation by year observations and ask whether exposure to digital technology predicts curriculum updates:

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

where k indexes curricula, j training occupations, t calendar years, and τ the first year a curriculum is observed. The dependent variable is a dummy for a training occupation's curriculum updating over time, set to zero for years where the curriculum does not undergo a change. The independent variable of interest is $\text{Tech}_{k,[t-25;t-20]}$, measuring each training occupation's exposure to digital technology, as revealed by the logarithm of the number of textually linked digital breakthrough patents over a five-year window 20 years prior. Calendar year fixed effects (γ_t) absorb year-specific variation in curriculum updates (for example for institutional reasons) and in the number of patent linkages. We control for the year of the training occupations' initial curriculum ($\theta_{j,\tau}$) in five year bins since training occupations j enter the dataset at different points in time. In some specifications, we further add broad occupation or broad occupation by year fixed effects ($\zeta_{J(\times t)}$). Lastly, we add occupations' initial employment size in 1975 ($\frac{E_{jt0}}{E_{t0}}$) to control for the possibility that larger occupations are more likely to receive curriculum updates.[16] Standard errors are clustered by occupation (259 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 shows estimates of equation (1), with the top panel showing unweighted models and the bottom one models weighted by initial occupational employment shares. Across all specifications, we find technology exposure spurs curriculum updates: a doubling in the exposure increases the probability that a curriculum is updated by 0.42–0.50 percentage points in the unweighted models, and 0.80–0.84 percentage points in the weighted models.

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

Since the estimates are robust to controlling for broad occupation fixed effects (columns 2 and 6) and broad occupation by year fixed effects (columns 3 and 7), technology exposure also spurs curriculum updates *within* the five broad occupation groups. Further, results are robust to controlling for occupational employment size (columns 4 and 8), addressing the concern that larger occupations may be more likely to receive updates.[17]

As reported in Appendix Table B3, digital technology exposure has an unweighted standard deviation of 2.58 in our panel data. This implies that a standard deviation increase in technology exposure increases the annual probability of a curriculum update by 1.24 percentage points (0.48×2.58, using the estimate from column 4). This effect is sizable since on average the annual probability of curriculum updates is 3.8% (shown in Table 2) When using weighted models, we find slightly larger effect sizes: the effect on the curriculum update probability of a standard deviation increase in technology exposure is 2.17 percentage points (0.83×2.61, using the estimate from column 8), compared to a weighted mean of 4.1%.[18]

As a complement to the yearly panel used in equation (1), we use the dataset of initial curriculum observations—i.e. the first time a curriculum is observed. This allows us to consider how many years it takes for the curriculum to be updated for the set of updated curricula:

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

where k indexes curricula, j training occupations, and τ the first year a curriculum is observed. The dependent variable is the number of years it takes for a curriculum to be updated, conditional on an update being observed at some point in time.[19] The independent variable of interest is each curriculum's initial technology exposure, defined as before. We control for the year of the initial curriculum in five year bins ($\theta_{j,\tau}$) and, in some specifications, broad occupation fixed effects (ζ_J) and initial occupational employment size in 1975 ($\frac{E_{jt_0}}{E_{t0}}$).

Compared to the first model, this second model informs on the intensive margin only: given that a curriculum is updated, does the number of years it takes for the update to occur

[17]Our findings are unaffected by removing patents held by German inventors.

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

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

depend on technology exposure? Here, we expect $\beta < 0$, reflecting that technology-exposed occupations are updated more rapidly.

We find similar effects for the intensive margin compared to the overall effect. Intensive margin estimates are reported in Table 6: conditional on a curriculum being updated, the update occurs more rapidly for technology-exposed occupations. This is true in unweighted (panel A) and weighted models (panel B), and robust to controlling for broad occupation fixed effects and occupational employment size. For example, the unweighted model reported in column 3 implies a doubling of technology exposure predicts the update arrives around 8 months ($= -0.63 \times 12$ months) earlier. Scaled by the unweighted standard deviation of digital technology exposure in these curriculum-level data (reported in Appendix Table B3), this implies a one standard deviation increase in technology exposure reduces the time to an update by around 1.6 years (-0.63×2.61). Since the average time to curriculum update shown in Table 2 is 15.3 years (with a standard deviation of 7.8 years), this is a moderately-sized effect. This suggests both the extensive margin (whether the curriculum is updated at all) and intensive margin (how rapidly the update occurs) are impacted by technology exposure, though the former is quantitatively more important.

In the Appendix, we document that these findings are robust to changes in how technology exposure is constructed. Appendix Table B6 shows that our results are similar and remain statistically significant when only using the exam section of curricula to construct patent links, although estimates are lower and less precise. The exam section arguably reflects the high-stakes component of the curriculum by describing skills that are subject to examination, but it constitutes only around 11% of the curriculum text on average (see Appendix Table B1), reducing signal and thus the size and precision of the estimates. However, our results indicate that when the skills tested in the exam are more exposed to digital technology, the curriculum is more likely to be updated. Appendix Table B7 highlights that updates also arrive more rapidly. Appendix Table B8 further shows that our results are upheld but estimates are somewhat lower when using all breakthrough patents to construct technology exposure rather than only patents related to digital technology. This suggests that exposure to *digital* technology has stronger impacts on curriculum updates over this period, but exposure to other technologies is not canceling out this effect by slowing down the update process.

In Table 7, we further investigate whether these results are driven by any particular type of curriculum change. Specifically, we consider the subset of curriculum changes which are not accompanied by any occupational renaming, aggregation, or segregation; and the subsets of curriculum changes which are accompanied by each of these three additional changes.[20] For each of these subsamples, we estimate equation (1) to test whether technology exposure spurs curriculum change of these specific types. Table 7 shows that digital technology exposure predicts curriculum updates *not* accompanied by any occupational change (panel A), as well as curriculum updates accompanied by occupational renaming (panel B), occupational aggregation (panel C), and occupational segregation (panel D). While technology exposure significantly predicts all four types of curriculum updates, effect sizes differ somewhat: considering that the annual average probability of a content update without any accompanying occupation change is higher (2.1%, see Table 2) than the probability of a content change involving other occupational change (1.5% for renamings, 1.0% for aggregations and 0.3% for segregations), the technology exposure effect is larger for curriculum updates involving renamings, and even more sizable for updates involving aggregations and segregations. Appendix Table B9 shows similar results when weighting models by occupational employment shares.

Appendix Figure A3 shows a Kaplan and Meier (1958) survival plot of curricula that are updated at some point during our observation window, separately for high- and low-technology exposed curricula. In our context, survival means the curriculum is *not* updated. This methodology accounts for right-censoring. The plot confirms that high-technology exposed curricula are updated more rapidly. For example, 15 years after a curriculum is first observed, around 70% of the curricula with low technology exposure have survived (i.e. have not yet been updated), versus only 50% for those with high technology exposure.

Finally, to explore the time lag between technology exposure and curriculum updates, we use local projections (Jordà, 2005). We relate curriculum updates to technology exposure and a set of controls in our panel of training occupation k by year t observations by estimating the following model separately for time intervals of increasing length T:

$$\mathbb{1}(\text{Update})_{kj[t+T]} = \beta \text{Tech}_{k,[t-5;t]} + \delta_1 \text{Tech}_{k,[t-5;t-10]} + \gamma_t + \theta_{j,\tau} + \delta_2 \frac{E_{jt_0}}{E_{t0}} + \zeta_{J\times t} + \varepsilon_{kjt} \quad (3)$$

The β coefficient in each regression captures how initial technology exposure impacts curriculum updates over time windows of expanding length T. We control for prior technology exposure (captured by a five-year lag, $\text{Tech}_{k,[t-5;t-10]}$) to avoid serial correlation in technology

[20] As noted in Section 2, renamings can co-occur with aggregations and/or segregations: in fact, around 85% of aggregations or segregations are accompanied by a renaming of the occupation. Aggregations and segregations may also co-occur.

exposure impacting our estimates. As before, we add year fixed effects (γ_t) and initial curriculum year fixed effects ($\theta_{j,\tau}$); and in the most saturated specification additionally control for initial occupational employment size in 1975 ($\frac{E_{jt_0}}{E_{t0}}$) and broad occupation by year fixed effects ($\zeta_{J\times t}$). We cluster standard errors by occupation.

Figure 12 plots these local projection estimates, showing that technology exposure does not have an immediate effect on curriculum updates: β coefficients are very close to 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 subsequently decreasing somewhat until year 25. While noisier, the time pattern of exposure looks qualitatively similar when we use the most saturated model. These results bolster confidence in the 20-year lag we use to define exposure to breakthrough technology.

3.2 Changes in curriculum content

We have so far considered the occurrence and speed of curriculum updates. We now turn to changes in training content, which we expect to evolve towards tasks and skills which are more complementary to digital technology. In particular, we examine whether workers are using more digital technologies and social skills in their vocational training, are learning fewer routine tasks, and more complex tasks. We also separate curriculum change into newly added and 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

To study changes in skill content, we estimate descriptive models of the following form:

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

in the yearly panel where skill_{kjt} is a skill measure of curriculum k for training occupation j in year t. β is the coefficient on a linear timetrend t, capturing the average annual change in skill content across curricula expressed in standard deviations. Since content changes by definition occur at the intensive margin, we estimate equation (4) for the subset of updated curricula, i.e. those which have potentially seen a change in their skill content. We control for 5-digit occupation fixed effects δ_j to take into account the different occupational composition of curricula over time.[21] Standard errors are clustered by 5-digit occupation. Because of the inclusion of detailed fixed effects, the first five years of data (when only a a handful of curricula are updated) are dropped: the resulting regression models cover 1976–2021.

We also estimate equation (4) separately for training occupations with above-median and at or below-median technology exposure, which we measure in the year a curriculum was first observed to avoid including endogenous changes in curriculum content. We expect the estimated β to be positive, and more so for occupations which are highly exposed to digital technology.

We first estimate this model to document the emergence of keywords related to digital technology and to social skills in vocational training curricula. Increased mention of digital technology in curricula would help further validate the importance of technological advances for curriculum updates, and indicate workers are being trained to work with these technologies. Social skills, on the other hand, are particularly complementary to digital technology (Deming, 2017): we therefore expect a rising importance of social skills in curricula, especially when they are highly exposed to technology.

For digital technology use, we consider the occurrence of words starting with "digital", "software", or "computer". For social skills, we simply use the occurrence of words containing "team". Descriptives are reported in Appendix Table B5. We again estimate equation (4), with the dependent variable the occurrence of these digital or team keywords, among updated curricula.

The top panel of Figure 13 plots the average annual change in digital technology use over time (controlling for 5-digit occupation fixed effects as before). In the three separate sub-figures on this row, this use is measured as a dummy for the occurrence of digital keywords in curriculum text; as the share of digital keywords in curriculum text; and as the absolute number of digital keywords in curriculum text. For each of these measures, there has been an increase in digital keywords over 1976–2021. Moreover, this increase is mostly seen in curricula which are highly exposed to digital technology, increasing confidence in our measure.

For example, digital keyword occurrence increases by 1.7 percentage points annually among updated curricula, indicating that curriculum texts increasingly include one or more digital keywords. The number of digital keywords as a share of all curriculum text tokens increases by around 0.04 percentage points cumulatively over the entire period (0.009/1,000

[21] This results from the growing number of curricula, see Figure 8.

$\times$ 100 percentage points annually $\times$ (2021$-$1976)): this is entirely driven by curricula which are highly exposed to digital technology, for which the cumulative increase in the share of digital keywords is 0.07 percentage points (0.015/1000 $\times$ 100 $\times$ (2021$-$1976)). Highly technology-exposed curricula add close to 0.8 digital keyword annually to their curriculum texts, with no change observed for less technology-exposed curricula.

The bottom panel of Figure 13 shows that social skills have become significantly more important in vocational training curricula over time, as well, whether measured as the occurrence of team keywords, the share of team keywords in total curriculum text, or the absolute number of these keywords. Across all three measures, the rising importance of social skills is more pronounced in curricula highly exposed to digital technology, with around 0.4 such keywords added annually on average for highly exposed curricula and no perceptible change for less exposed curricula.[22]

We next consider how curriculum updates changes routine 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 these routine tasks (e.g. see Autor et al. 2003, 2006; Autor and Dorn 2013; Goos et al. 2014). This implies that vocational training curricula should become less routine task intense over time if digital technology is an important driver of curriculum updates. We also expect that the decline in routine task intensity of curricula is more pronounced among highly technology-exposed occupations.

To measure the task content of training curricula, we again leverage NLP methods. In particular, 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 next measure cosine similarity of the training curricula vectors (as constructed before) to these task vectors: a high cosine similarity between a curriculum-task pair implies this curriculum is textually similar to this task.

We define routine task intensity by summing each curriculum's cosine similarity to the two routine tasks and then subtracting the sum of its similarities to the three non-routine tasks. That is, the routine task intensity (RTI) for each training curriculum k is measured

[22] Appendix Figure A4 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 patents. Appendix Table B10 lists specific O*NET items used for each of the five task groups.

as

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

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

Appendix Table B11 shows the most and least routine intensive curricula. Among the most routine intensive are curricula for Confectioners, Embroiderers, Glassmakers, Dressmakers, Clothes tailors, Bakers, and Basket makers. By contrast, among the least routine intensive curricula are those for Sports specialists, Personnel services clerks, Market and social research specialists, Marketing communication clerks, and Event managers.[24]

We document how the routine task intensity of curricula evolves over time by estimating (4), using curriculum RTI as the dependent variable, standardized to have a zero mean and unit standard deviation across curricula.

Figure 14 plots estimates of β (and 95% confidence intervals), showing a clear downward trend in the routine task intensity of vocational training curricula overall. Annually, routine task intensity decreases by 0.041 standard deviations, amounting to 1.8 standard deviations cumulatively over 1976–2021. Further, this trend is more pronounced for more technology-exposed occupations, where the routine intensity of curricula declines by 0.058 standard deviations annually (i.e. 2.6 standard deviations cumulatively over 1976–2021), compared to 0.023 standard deviations annually (1.0 standard deviation cumulatively) for less technology-exposed curricula. This implies that curriculum updates equip workers with training in less routine-intensive tasks, especially when these curricula train for occupations that are highly exposed to digital technologies.

These trends are present in both production and service occupations, as Figure 14 also reveals. While routine task intensity diminishes significantly across the board, the decline is somewhat more pronounced among production occupations, which constitute 65% of training curricula. However, the decline in routine intensity for technology-exposed curricula is very similar in magnitude for both production and service occupation (although the estimate for

[24] Appendix Table B12 shows the most and least routine intensive curricula separately for each of the five broad occupation groups. Appendix Figure A2 shows that routine task intensity is negatively correlated with occupational employment growth, as expected.

service occupations has a larger confidence interval).[25,26]

Lastly, in Appendix Figure A6, we show that curricula are also becoming more complex, as defined by the share of curriculum words that are not in a typical eighth-grader's vocabulary (Dale and Chall, 1948). Autor and Thompson (2024) argue that this complexity score is a measure of expertise, with more complex words reflecting skills or tasks that are less easily performed by a broad group of workers, and therefore more expert. In practice, at the curriculum level this complexity score is highly correlated with our measure of routine task intensity ($r = -0.62$).

3.2.2 New skill emergence and skill removal

The changes in vocational skill content we document may arise from new skills being added when curricula are updated ('new skill emergence'), from pre-existing skills receiving a different weight ('intensive margin skill changes'), or from being removed ('skill removal'), or a combination of these three.[27] These may have different consequences for workers: simply acquiring a narrower skill set than prior trainees (for example because some tasks can now be automated), is less likely to be beneficial, relative to (also) acquiring new expertise.

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

Figure 15 highlights that curriculum updates are characterized by substantial amounts of word removal as well as new word addition. Across all five occupation groups, a curriculum update involves some 150 distinct words being removed and around 180 distinct new words being added (panel A), corresponding to around 35 to 40% of the total counts of distinct

[25] Appendix Figure A5 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] Buehler et al. (2025) who study curriculum design by considering removed and added word shares in Swiss curricula.

[28] In our baseline results presented here, we count as new any word that has not occurred in the previous curriculum of the training occupation, and as removed any word not found in the newly updated curriculum. 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.

curriculum word (panel B).[29]

Importantly, intensive margin skill changes, skill removal, and new skill emergence play distinct roles in changing curriculum skill content. Figure 16 illustrates this for changes in non-routine task intensity (panel A) and changes in complexity (panel B).

In panel A, the non-routine task intensity of the remaining part of the previous curriculum is shown, and this is plotted against the non-routine task intensity of three separate components of the new curriculum on the vertical axis. These three components are the words present in both curricula ('remaining words'), words removed in the curriculum update, and words added in the curriculum update. Each observation is a curriculum update, and a local polynomial plot is shown for each component. Observations lying on the 45-degree line indicate a particular part of the new curriculum had the same routine task intensity as the previous curriculum's constant words, therefore not impacting the previous curriculum's routine task intensity. Observations lying above (below) the line are higher (lower) in non-routine task intensity than the previous curriculum, shifting it to become less (more) routine task intense. Panel B shows the same information but for the curriculum's word complexity, measured as the share of words that are categorized as complex.

Figure 16 shows that newly added words play an outsized role in increasing curriculum non-routine task intensity, as well as in increasing curriculum complexity: the orange-colored data lie most strongly above the 45-degree line in both panels. At all levels of previous non-routine intensity and complexity of the previous curriculum, newly added words make the updated curricula more non-routine intense and more complex: this effect is particularly pronounced among curricula which were least non-routine intensive and the least complex to start with. Skill change along the intensive margin, as represented by changing frequency of remaining words; and skill removal play a role as well, though to a lesser extent. Intensive margin skill change also tend to increase non-routine task intensity, especially for curricula which are already relatively non-routine intensive; and are mostly neutral for curriculum complexity. Skill removal has a neutral effect on non-routine task intensity on average, but this differs across curriculum non-routine intensity. Removed words are more routine intensive for the least non-routine curricula— therefore increasing non-routine task content. However, for the most non-routine curricula, removed tasks actually make the curricula somewhat more routine intensive. All in all, the results in Figure 16 make clear that curriculum

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

content change arise from both new skill emergence and skill removal: below, we directly test whether the former reinstates labor's expertise for new labor market entrants with updated skills and the latter erodes it for occupational incumbents trained in the previous curriculum.

4 The labor market impacts of curriculum updates

The evidence above establishes that updates in vocational training curricula are spurred by technological advances, and that this is accompanied by training content evolving towards skills that are more complementary to digital technology, especially through the addition of new skills. But does having these updated skills improve worker post-training labor market outcomes? If changes in training allow workers to adjust to changing skill demands, we expect workers with updated training to fare better in the labor market than their counterparts who have been trained in the old curriculum. We also expect occupational incumbents to experience skill obsolescence when workers with new skills enter their occupation. We explore those implications here.

4.1 Sample construction

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

We observe workers' apprenticeship training spells, which is how we identify when workers start and complete their training program, as well as which occupation they are trained in. In combination with our curriculum dataset, this allows use to determine which curriculum vintage each worker is trained in. For workers who completed their training before 1975, we only observe that they hold a vocational training degree, without information on when it was

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

obtained or in which occupation. Therefore, we restrict our sample to workers observed in apprenticeship training from 1975 onward. This does not come at the loss of much data since most curriculum change occurs from 1990 onward. We further restrict the sample to Western Germany, because we only observe workers from Eastern Germany after 1992 and training curricula before German reunification apply to West German apprentices only. Appendix D provides further details on data construction.

Since training occupations do not correspond one-to-one with KldB occupational codes provided in the SIEED data (as discussed in Section 2.1), we proceed as follows. For KldB occupations (henceforth: occupations) comprised of multiple training occupations, we consider the workers employed in that occupation as having updated skills when at least one of the underlying training occupation curricula was updated. For training occupations linked to multiple occupations, we classify workers employed in all associated occupations as having updated skills.In the analyses below, we use data on both labor market entrants (Section 4.2) and occupational incumbents (Section 4.3).

For descriptives of occupational employment evolutions (including when using these as a control variable) discussed in Section 2.1, we use SIAB data (Graf et al., 2023).[31] These data contain the same variables as the SIEED data 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 2.0 million in SIAB data) and spells (173 million compared to 77 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 leverage a difference-in-differences event study design comparing outcomes between cohorts of workers with old skills ('old-skilled workers') and cohorts of workers with new skills ('new-skilled workers') in occupations with training updates to worker outcomes in occupations where no such update occurred around the same time. We consider labor market entrants,

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

who we define as vocationally trained workers in the first 5 years since the end of their training. We estimate

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

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 has seen an update of its training curriculum during our time window: for each separate training update, this separates our treatment group (workers trained in occupations with a curriculum change) from our control group (workers trained in occupations without curriculum change).[32] Specifically, control group workers are those trained in occupations without curriculum updates in a window of 5 years before and 5 years after the treatment occupation received an update. c denotes cohorts of workers defined by the start year of their vocational training program relative to the year of the potential curriculum change. We normalize $c = 0$ to represent the first cohort trained in the new curriculum: as such, 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 received an update, i.e. $c = [-5, 5]$.

Treatment is staggered because different curricula are updated in different years, so we cannot use the two-way fixed effect estimator to uncover the parameters of interest (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).[33] As a result of this stacking, 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 is updated more than once. Therefore i indexes individual workers by curriculum update ('event'), j indexes occupations by event, and t indexes calendar years by event.

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

[33]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. (2023).

For each event, we draw all treated workers and a twice as large random sample of control workers — with a minimum of 200 control workers if there are fewer than 100 treated workers. We restrict the pool of control workers to those in training occupations with the same typical training duration as each treated occupation to avoid confounding employment with training spells. We drop events with fewer than 20 treated workers in our data: this leaves a total of 379 curriculum update events and 295,348 unique workers, 152,989 of which are treated and 142,359 of which are controls.

Note that this approach uses repeated cross-sections of worker cohorts rather than a worker panel, as pre-training (i.e. pre-treatment) outcomes within workers do not exist. Hence, the first difference in our differences-in-differences (DiD) strategy is the difference in outcomes between 'old-skilled' cohorts (i.e., workers trained in the old curriculum) and 'new-skilled' cohorts (i.e., workers trained in the new curriculum) of the same occupation. The second difference is the difference in outcomes between treated workers who were trained in occupations that have seen an update and control workers who were trained in occupations that have not seen an 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), and educational upgrading. For the case of 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 controls with event dummies as is standard in stacked designs. We cluster standard errors at the level of treatment: training occupation by event.

Estimates of β_c can be interpreted as causal effects under the identifying assumptions of (i) parallel trends in the absence of curriculum updates, (ii) no anticipation of the curriculum update by (prospective) trainees (nor anticipatory reactions by firms), and (iii) SUTVA. Below, we provide empirical support for these assumptions in several ways. First, we show there are no significantly distinct pre-trends in worker outcomes. Further, one may be concerned 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 any wage impacts need not reflect returns to new skills. In Appendix E we therefore extensively consider changes in trainee composition as well as apprenticeship application numbers, finding no evidence of changes around curriculum updates, consistent with parallel trends and no anticipation. Last, we show that positive wage effects are driven by faster wage growth for treated cohorts, not a deterioration for control group cohorts as would be expected in the case of a SUTVA violation. We also confirm our results are robust to excluding from the control group those occupations with the highest worker mobility from the treated occupations.

4.2.2 Wage impacts

Table 8 shows descriptives for our sample of vocationally trained labor market entrants within the first five years after training completion and the firms they are employed in, based on SIEED data. Vocationally trained labor market entrants are 23 years old on average, and 40% are female. Daily wages are 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. Last, workers are employed in relatively large firms (559 workers on average), although the median firm size is 40 workers. Appendix Table B13 shows corresponding descriptives for the stacked sample, separately for the $\tau = -1$ cohorts of treated and control group workers.

Figure 17 provides estimates of equation (5), using log daily wages as the dependent variable and multiplying β_c coefficients by 100 for legibility. Reassuringly, there is no evidence of pre-trends, consistent with treated and control group worker cohorts being on similar wage trajectories before the curriculum reform. We find significant positive wage effects from curriculum updates, measured over workers' first five years after graduation from vocational training. These effects are up to 2.2% 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 are comparing workers trained for the exact same occupation, but with an updated curriculum. We find positive wage effects starting from the third cohort trained in the new curriculum onward. Grace periods in implementing the new curriculum, discussed above, may contribute to the delay. This is particularly true since impactful and technology-driven curriculum changes, for which we would expect larger wage returns, are more likely to be granted grace periods. The positive wage returns highlight that educational content is racing to keep up with changing skill demands, and graduates with updated skills earn a significant wage premium. Appendix

Figure A9 shows predicted log wages for treated and control group workers, highlighting that the found wage returns are the result of more rapid wage growth for treated worker cohorts after the curriculum update, not slower wage group for control group workers. As such, the wage premium for obtaining new skills reflects an absolute improvement, not just a relative one.[34]

Appendix Table B14 provides the corresponding estimates for our main specification in column 1. Column 2 excludes the first year after graduation, in case starting wages for vocationally trained workers in Germany are relatively rigid, with graduates having little bargaining power over their wages. However, we do not find larger estimates in this specification, indicating that starting wages are also positively impacted by curriculum updates.

In Appendix E, we document that curriculum updates do not impact trainee composition, suggesting that wage increases are not driven by improvements in trainee characteristics. We also do not find any changes in program selectivity, as proxied by the share of unfilled apprenticeship positions or unsuccessful apprenticeship applications. Further, Appendix Figure A8 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 employment.

4.2.3 Mechanisms

To inform on the mechanisms underlying improved wage outcomes for workers with updated skills, we first consider how wage impacts differ by updated occupations' technology exposure. Curriculum updates may occur for various reasons, but exposure to technology is an important driver, as Section 3.1 documents. If curriculum updates provide a skill set that is more complementary to new technologies (see Section 3.2), we would expect to see wage returns of curriculum updates for workers trained in technology-exposed jobs.

Figure 18 reports wage returns to curriculum updates separately by technology exposure, defined as the exposure of the treated occupation to patents being above or at or below the median exposure, as before. We confirm that curriculum updates for highly technology-exposed occupations yield wage returns for new-skilled worker cohorts, and these wage premia

[34] Our results are very similar when we restrict control group occupations to be from different 2-digit occupations than treated occupations, reducing concerns that there are spillovers to the control group.

are higher than for less technology-exposed occupations, especially for later cohorts. While no difference is visible for the first two 'new-skilled' cohorts, cohorts trained in occupations with high technology exposure two to five years after the curriculum update earn 2.4% (cohort 2), 3.1% (cohort 3), 4.1% (cohort 4), and 4.2% (cohort 5) higher wages over the first five years of their careers than does the last cohort trained in the old curriculum ($c = -1$). Corresponding estimates for workers trained in occupations with low technology exposure are smaller than 1% and not statistically significant.

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 to the curriculum's technology exposure. Figure 19 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 A11 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. Examples of curricula in the bins with low exposure are Orthopedic shoemaker, Bicycle mechanic, and Stone mason and stone sculptor for production; and Barber and Tourism and leisure clerk for services. Curricula in medium-exposed bins include Hydraulic engineer, Carpenter, and Technical assembler for production; and Warehouse logistic specialist, Marketing communications clerk, and Medical assistant for services. Curricula in 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. In both figures, there is a clear upward relationship between the technology exposure of a curriculum update and the resulting wage return. This relationship holds within production as well as within services occupations, even though wage returns are typically higher across the board for production occupations.

Taken together, this evidence suggests that skill updates spurred by advancing technology impart larger and longer-lasting labor market advantages than updates spurred by other factors. Appendix Figure A10 plots predicted log wages for treated and control group workers by technology exposure, showing that wage growth for workers trained for technology-exposed occupations accelerates after the curriculum update.

We next study the impacts of curriculum updates on annual wage income rather than log daily wages: these annual effects include any impacts on days worked. Estimates are shown in panel A of Appendix Figure A12. As for daily wages, we find significant annual income increases from training in updated curricula highly exposed to technological advances. Estimated effects are similar in magnitude to the daily wage impacts (up to 4.1% higher annual wages over the first five years post training), suggesting that the main margin of adjustment is through wages earned rather than days worked as expected among this group of early career workers. Models estimated for annual days in employment, shown in panel B of Appendix Figure A12, confirm only very small impacts on the employment margin which are almost never significant.[35]

To consider whether these labor market advantages accrue from worker differences in early career paths, we use occupation, industry, and firm mobility as outcomes in equation (5). Do skill updates make workers more likely to remain in the occupations they were trained for? Do wage returns emerge within the same firms (and industries and occupations), or do they result from workers with new skills having different job mobility patterns?

Figure 20 displays these mobility estimates, considering mobility outcomes relative to the worker's apprenticeship position: that is, we consider whether workers have moved out the 4-digit occupation, the 3-digit industry, or of the firm where they did their apprenticeship. (Results are similar when instead considering year-on-year mobility, i.e. relative to the occupation, industry, and firm in which they did their apprenticeship until their first move, then relative to their new position for the second move, and so on.)

A consistent picture emerges: curriculum updates do not have a measurable impact on industry or firm switching, but they do reduce the probability of workers leaving their training occupation. The reduced occupational mobility pattern aligns with the timing of wage returns, becoming stronger for the later cohorts. Relative to their training occupation, cohorts with updated skills are up to 3.1 percentage points less likely to switch occupations over the first five years of their career. This is a moderately-sized effect compared to the baseline probability of occupation mobility of 35% over the first five years of the career, shown in Table 8.

Although new-skilled workers do not have differential rates of firm mobility, as shown in panel of A of Figure 20, 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

[35]Given workers' very high labor force attachment, we only consider workers with at least some income: those who do not work at all need not be unemployed but may also engage in other activities, such as a gap year abroad. When we separately estimate models for the probability of having any earnings, we do not find any impact of curriculum updates on this margin.

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.)

To gain insight into how the wage effects of curriculum updates evolve over the first five years of workers' careers, we estimate the model separately by workers' potential experience. Estimates are plotted in Appendix Figure A13. For example, the series labeled '3 years post training' considers how log daily wages in the third year after vocational training completion evolve across worker cohorts. Comparing across these subplots reveals that wage returns accruing relatively consistently over the first five years of the career. An additional benefit of the estimates by potential experience is that our baseline specification could contain spillover effects because we consider wages averaged over the first five post-training years. In that specification, old-skilled cohorts trained before the curriculum update in part earn their wages over years when new-skilled cohorts have already entered the labor market, potentially impacting the estimates for $c < 0$. The estimates shown in Figure A13 are therefore better identified if there are spillover effects.

Lastly, we perform various additional (robustness) checks. First, our results hold when we control for firm fixed effects, whether defined as the firm where the workers did their apprenticeship training or where the workers are employed. Effect sizes are reduced by about 50% when adding the latter type of firm effect, confirming that moves to higher-paying firms are part of the underlying mechanism. Second, results are robust to excluding from the control group those occupations with the highest worker mobility from the treated occupations: while estimates become somewhat less precise, the effect sizes are very similar. This mitigates concerns about SUTVA violations. Finally, Appendix Figure A14 shows that wage effects are not driven by later educational upgrading (i.e. obtaining a university or 'Fachhochschule' degree, akin to a university of applied sciences degree) by new-skilled workers.[36] We also do not find any impacts on workers' probability of obtaining a Master craftsman diploma, either in the short or long run.

Overall, we conclude that skill updates provide labor market entrants with advantages through higher wages, coupled with increased occupational retention. These benefits are predominantly found for skill updates related to technological exposure, suggesting changes in within-occupational skill supply play an important role in keeping workers' expertise

[36] 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.

relevant in the face of 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 when new-skilled workers enter the occupation, interpreting declining wages as an indication of skill obsolescence. To do so, we construct a worker-level panel of vocationally trained workers, only including occupational incumbents, defined as having worked full-time in a single occupation for at least five consecutive years prior to a curriculum update in that occupation. We exclude apprentices and other workers not subject to social security contributions. We exploit the fact that we can follow individual incumbents over time by analyzing changes in their labor market outcomes before and after workers trained in a new curriculum enter the occupation. In particular, 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 $t = -3$ is the year of the curriculum update and $t = 0$ is the year where newly trained worker cohorts enter the labor market. Y_{ijt} is an outcome for worker i employed in occupation j in the years $t = [-5; -5]$. δ_i captures individual fixed effects, 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 (training occupation by event).

For each event, Update_j is a treatment dummy indicating whether occupation j has seen a curriculum update, and therefore an inflow of workers trained in a new curriculum. This separates our treatment group (incumbents in occupations with an inflow of new-skilled workers) from our control group (incumbents in occupations without an inflow of new-skilled workers). We match treated and control group workers based on their employment in production or service occupations, resulting in a sample of 1,050,828 unique workers, 561,422 in the treated group and 489,406 in the control group. All treated workers are exposed to new-skilled entrants in $t \geq 0$.

The parameters of interest are β_t, which estimate the effect of being exposed 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 the case of log wages, for example, we expect negative post-treatment estimates ($\beta_{t\geq 0} < 0$) if the competition with 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 the entry of 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 $t = -3$): 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 — with a minimum of 100 control incumbents if there are fewer than 100 treated incumbents. As before, control group workers are weighted by $\frac{1}{n_i}$, with n_i being the number of controls for treated worker i.

Appendix Table B15 shows descriptives for the sample of occupational incumbents. On average, incumbents are 42 years old, 36% are female, and they earn around 90 euros daily – 30% more than the early career workers we considered earlier. Unsurprisingly, they are somewhat less likely to switch occupations and industries than are early career workers, although firm mobility rates are still relatively high.

Panel A of Figure 21 shows that curriculum updates negatively affect wages for older occupational incumbents (ages 45–54, 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 3.0% for incumbents aged 45–54 and by 9.1% for incumbents aged 55–65. These wage losses experienced by older workers are informative 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 younger incumbents, we do not find wage losses: wage effects are zero for those aged 24–34 and 35–44. Incumbents do not work less in response to the entrance of new-skilled workers (panel B in Figure 21).

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 22. (Results are robust to considering more detailed occupation and industry classifications for switches.) 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 somewhat lower AKM fixed effects, shown in panel C of Figure 22. Our findings are consistent with Janssen and Mohrenweiser (2018), who consider the effect of a curriculum update involving CNC skills on the oldest incumbents, finding sizable wage losses (and only small and transitory non-employment effects), as well as moves to lower-AKM firms. We do not detect statistically significant differences between skill obsolescence effects for updates involving higher versus lower technology exposure, although the estimates for low exposure are much noisier.

These analyses contribute causal evidence of skill obsolescence. Our findings are in line 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.

5 Curriculum updates and firm capital investments

If curriculum updates improve workers' ability to work with new technologies, we would expect to see increased firm capital investment following curriculum updates. Previous work has shown a positive correlation between firms' participation in apprenticeship training and innovation in Switzerland (Rupietta and Backes-Gellner, 2019); provided causal evidence that supply reductions of apprentices reduce firm technology investments in Germany (Lipowski, 2024); and documented higher mentions of technology use in job ads for firms employing new-skilled apprentices for specific IT-intensive occupations in Switzerland (Schultheiss and Backes-Gellner, 2024). We identify causal effects of curriculum updates on investments in a difference-in-differences design and consider all observed updates, allowing us to compare those with high and low technology exposure.

We leverage IAB's Linked-Employer-Employee-Data (LIAB), which combines the IAB Establishment Panel survey with administrative employment information of all employees at surveyed firms on June 30 of each year. The IAB Establishment Panel is a large annual representative survey of establishments which contains information about investments. It covers West Germany since 1993, and is conducted at the workplace level (henceforth: firms). Employment information is based on administrative records reported to the social security insurance. We merge these data with our curriculum update events, and designate firms as treated if the curriculum is updated for at least one of their two largest vocational training occupations (in terms of their pre-update trainee employment share).[37]

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

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

$$Y_{it} = \sum_{t=[-3,6]} \beta_t \text{Update}_i \times I_t + \delta_i + \gamma_t + \varepsilon_{it}, \tag{7}$$

where Y_{it} is log investments or a dummy for positive investments (to consider the extensive margin) for firm i in the years $t = [-3; 6]$. Time t is normalized such that $t = 0$ is the year trainees enter vocational training under a new curriculum. δ_i 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 invest at least once in the time window and match firms on log investment levels in the pre-treatment periods (t-1, t-2, and t-3) using Mahalanobis distance matching (selecting the three nearest-neighbors). To deal with 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 9 shows firm-level descriptives for treated and control firms in year $t-1$, post matching. Our analyses are based on an unbalanced panel of 6,996 distinct firms in $t = -1$, 3,360 of which are treated. Treated firms on average employ 389 workers (243 for control firms), and are more likely to be in the manufacturing sector. Log investments have a high standard deviation of around 2.5, reflecting that investments are lumpy.

Panel A of Figure 23 shows the estimates. Log investments rise in treated compared to control firms once apprentices are being trained in the new curriculum, and continue being higher when new-skilled workers enter the labor market, with investment increases of up to 8%, corresponding to 3.2% of a standard deviation ($= 0.08/2.5 \times 100$). This suggests that both the need to train new skills and newly supplied skills indeed raise firm investments. Consistent with this interpretation, these investment increases are only observed for curriculum updates with high technology exposure, as seen in panel B of Figure 23.

Appendix Figure A16 shows equivalent estimates for the probability of investing, i.e. focusing on the extensive margin. Here, we find no effects, irrespective of technology exposure. This implies that investment effects are driven by the intensive margin, and by firms that were already investing.[38,39]

[38] When we combine the intensive and extensive margins by setting an investment change from zero to any positive investment to either a 1% or a 10% change (an approach suggested by Chen and Roth 2024), we find significantly positive effects, implying the intensive margin effects are meaningfully large.

[39] In this baseline, we define treatment status based on curriculum updates of firms' main training occupations: this is our most direct measure of being exposed to newly-trained workers, but limits the analyses

6 Conclusion

Do changes in educational content allow workers to adjust to evolving skill requirements from advancing technology? We consider this question in the context of vocationally trained workers in Germany, a large group of non college educated workers who are overrepresented among the middle- and low-paid jobs that have been highly exposed to (automation) technology. Leveraging a novel database of legally binding training curricula descriptions and changes therein over 1971–2021, we find that occupational exposure to technological change spurs educational updates, with training content evolving toward tasks that are more complementary to digital technology. This is largely driven by the emergence of new skills in vocational training curricula, highlighting that workers acquire new competences.

Using administrative employer-employee data for labor market entrants, we show that educational updates lead to improved wage outcomes for 'new-skilled' entrants compared to 'old-skilled' entrants, and a higher probability of remaining employed in the specific occupation the worker trained for. This indicates that workers can more effectively adapt to changing occupational skill demands, keeping their expertise relevant in the labor market. In contrast, older incumbent workers in occupations with skill updates experience wage declines when newly trained workers enter the labor market, compared to those in occupations without such updates. Younger occupational incumbents are more likely to switch occupations, and move to lower-paying firms. Consistent with technological change playing an important role, firm capital investments rise when firms are exposed to workers trained in updated curricula, especially when these curricula have more technological content.

These findings highlight that changes in educational content, not only increases in educational attainment, are an important tool for reinstating human expertise as technology advances. This effect is especially significant for non-college post-secondary education, which equips workers for a wide range of middle-class occupations. The rapid progress of artificial intelligence only reinforces this point.

We highlight that educational curriculum updates are common outside of Germany, as well. In the German context, vocational curriculum updates are jointly decided on by employer organizations, labor unions, and the Federal Institute for Vocational Education and Training: recent work suggests involving employers may be important for ensuring worker

to training firms. When we instead define treatment based on employment shares of occupations whose curricula are updated (allowing us to include all firms), we also find positive log investment effects (of up to 6%, which are driven by high-technology exposed occupations.

skills remain relevant for the labor market (Katz et al., 2022; Kahn et al., 2023). Moreover, coordination among employers may increase their willingness to train workers in new skills: in the absence of a legally binding curriculum adopted by all training firms, individual employers may be less inclined to provide such training. This is strengthened by the active role of labor unions and the Federal Institute for Vocational Training in these updates, since they emphasize that skill skills covered in the curriculum should not be firm-specific ones. Considering the role of such institutional forces in shaping skill acquisition and worker outcomes is a promising direction for future research.

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Figures

Figure 1: Distribution of Wages for Vocationally Trained Workers vs. Others

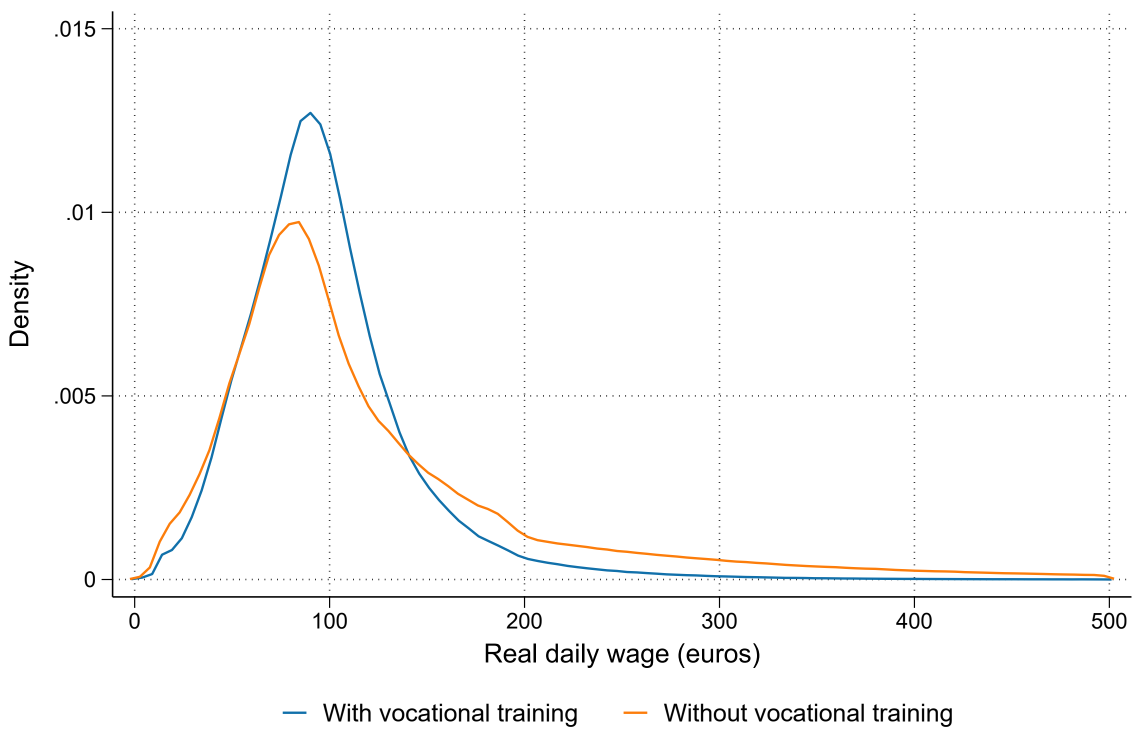


Figure plots the distribution of real daily wages (up to 500 euros) for vocationally trained workers versus all others based on SIAB data.

Figure 2: Distribution of Wages for Occupations With and Without Vocational Training Curriculum

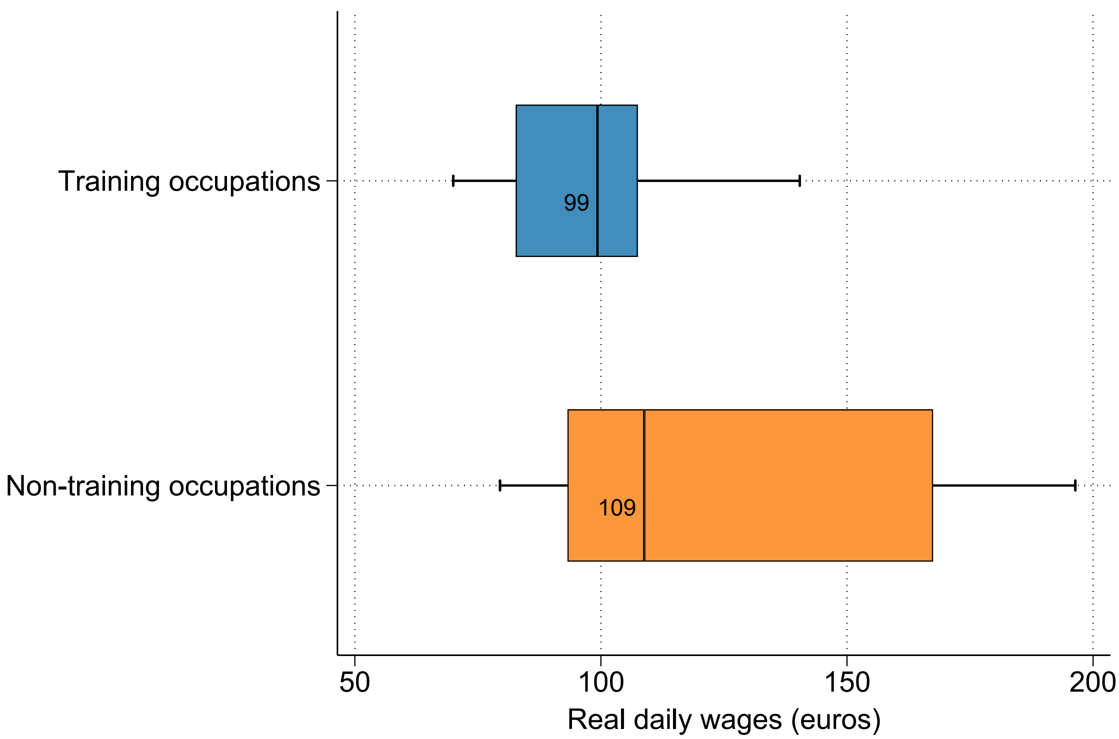


Figure shows a boxplot of real daily wages for occupations with and without a vocational training curriculum (base year for deflation: 2015) based on SIAB data. Vertical lines indicate the median; boxes reflect the interquartile range; and whiskers indicate the 10th and 90th percentiles. Occupations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

Figure 3: 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 4: 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 5: 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 6: 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 7: Number of Curriculum Changes by Year

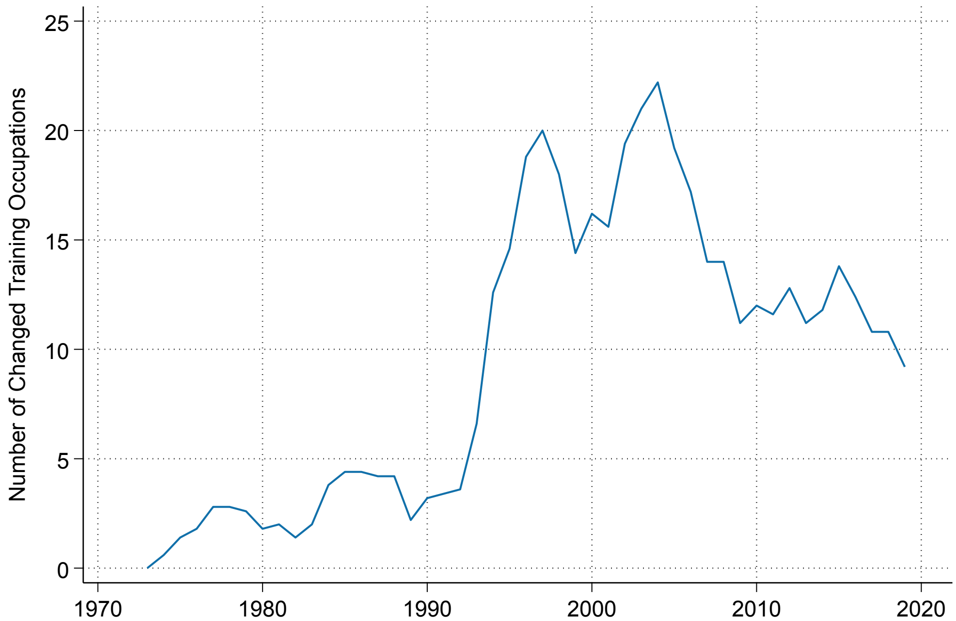


Figure shows the 5-year moving average of the number of curriculum changes by year.

Figure 8: Number of Training Occupations with Observed Curriculum by Year

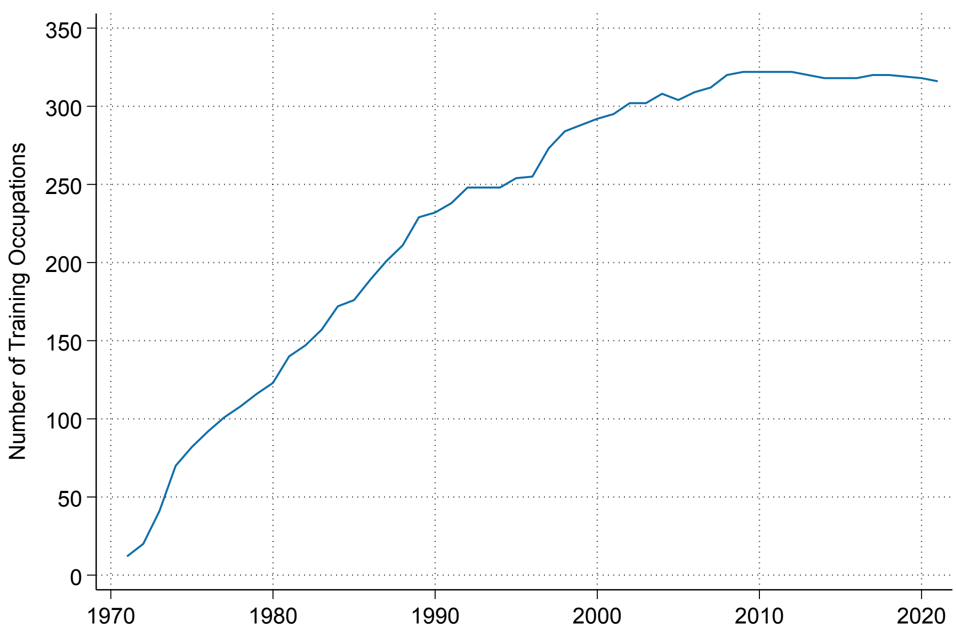
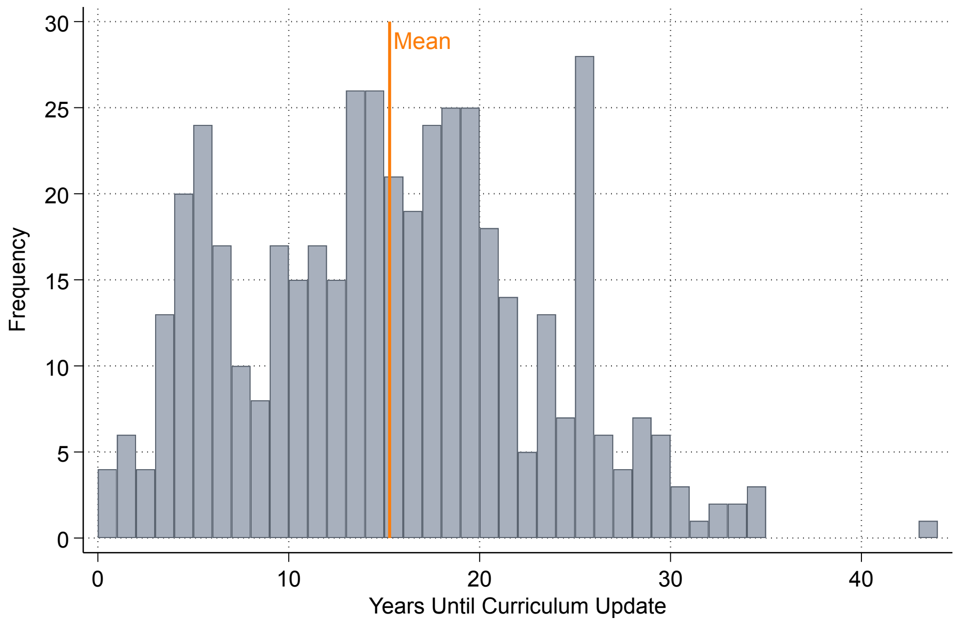


Figure shows the number of active training occupations in the national register after the introduction of the Vocational Training Act in 1969.

Figure 9: Years until Curriculum Update

A. Overall



B. By Broad Occupation Group

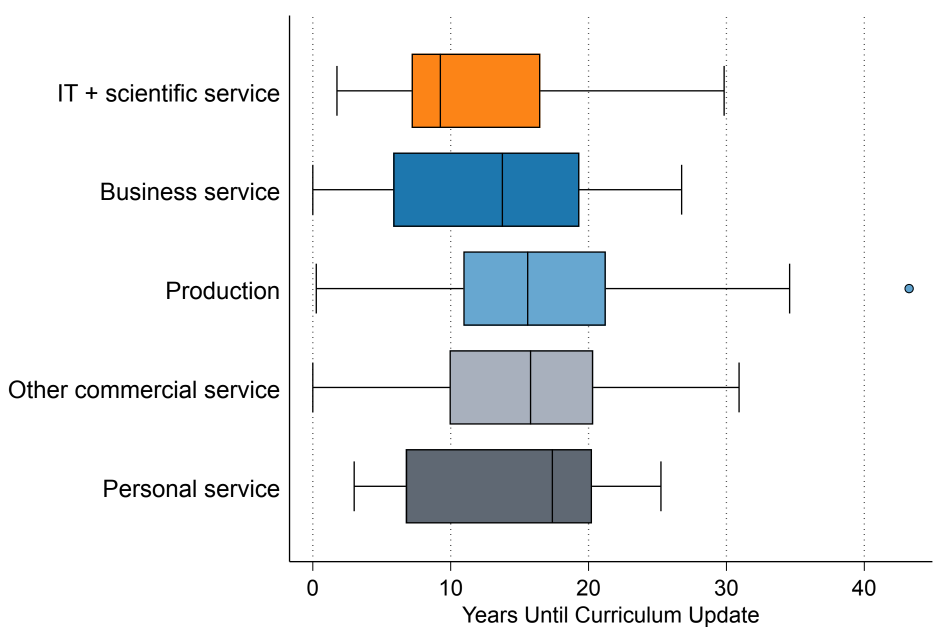


Figure shows the distribution of years until curriculum updates for initial training occupation observations ($N = 470$). Panel A shows the overall distribution across training occupations. Panel B shows a boxplot by broad occupation group. Vertical lines indicate the median; boxes reflect the interquartile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

Figure 10: Share of Breakthrough Patents by Technology Class

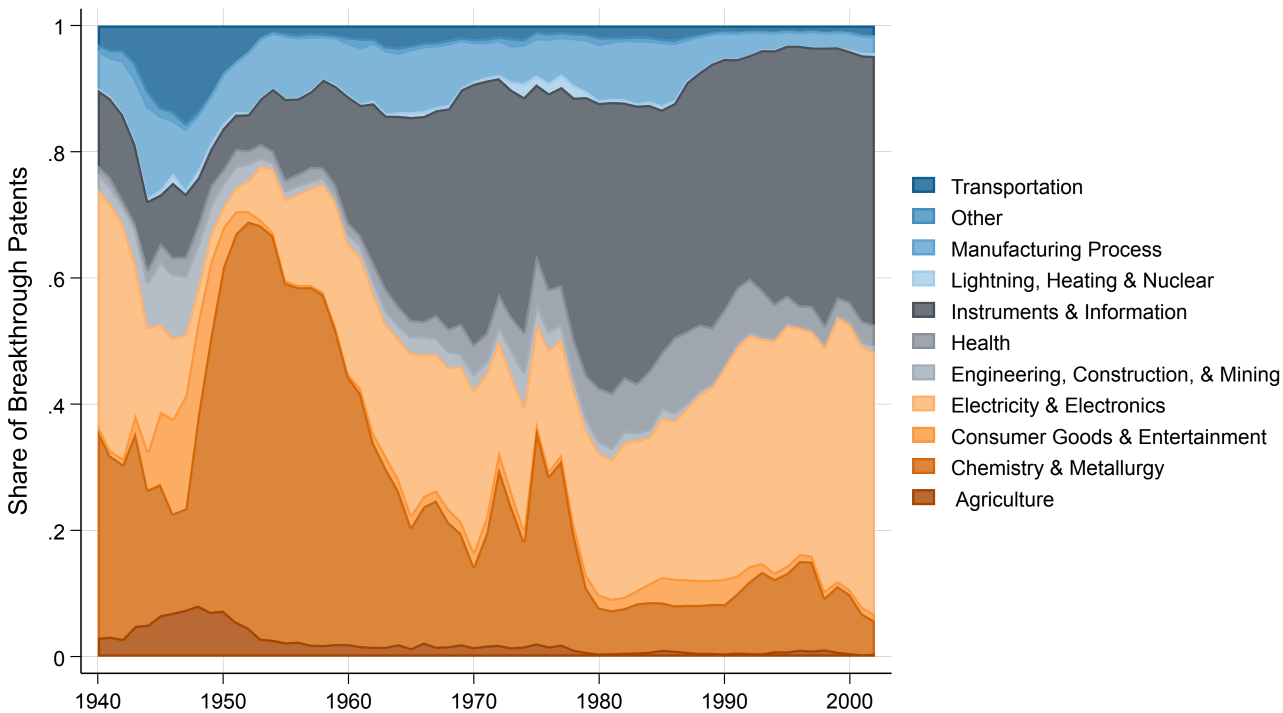
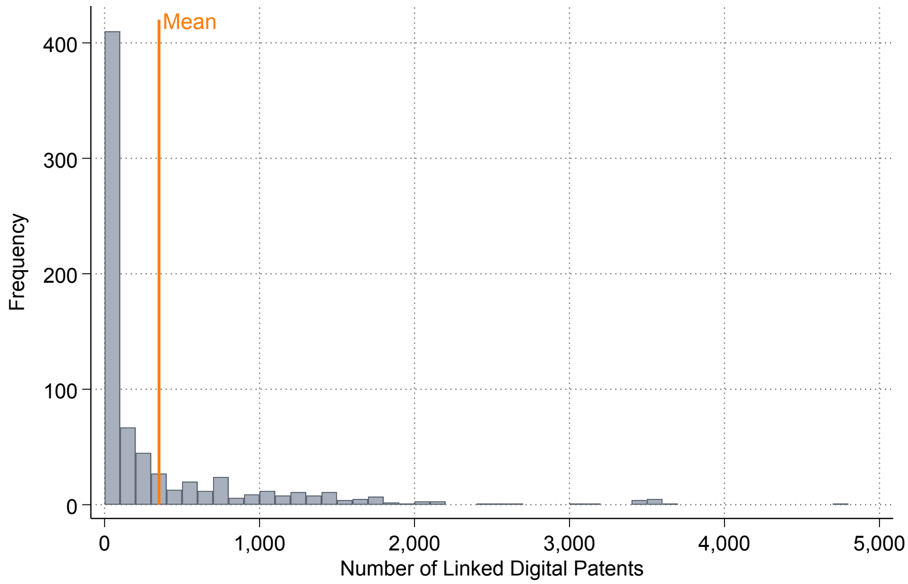


Figure shows the distribution of breakthrough patents across broad technology classes defined by Kelly et al. (2021). Over 1940–2002, we observe $N = 141,708$ breakthrough patents in Instruments & Information.

Figure 11: Digital Technology Exposure of Training Curricula

A. Overall



B. By broad occupation group

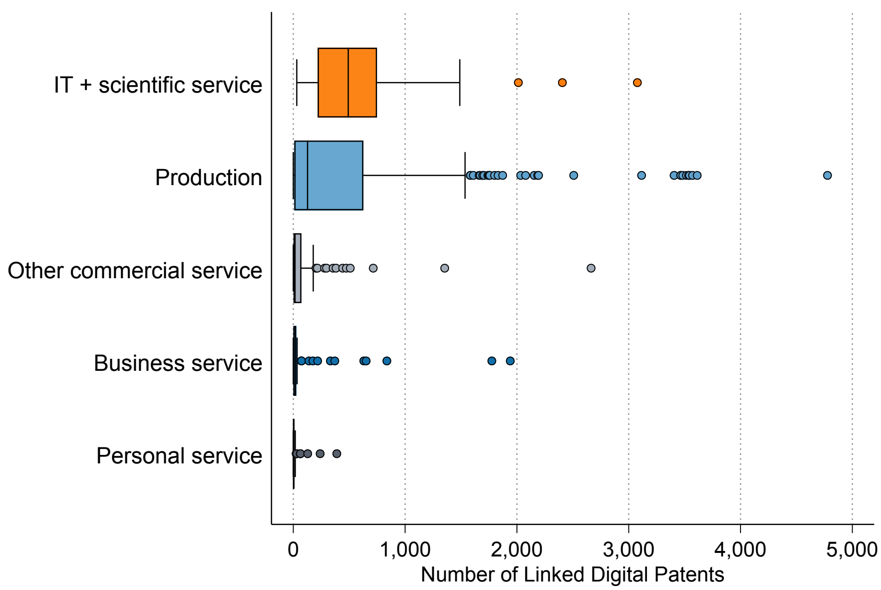


Figure shows the distribution of linked digital patent counts for initial training occupation observations ($N = 791$). Panel A shows the overall distribution across training occupations. Panel B shows a boxplot by broad occupation group. Vertical lines indicate the median; boxes reflect the interquartile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

Figure 12: Impacts of Digital Technology Exposure on Curriculum Updates Using Local Projections

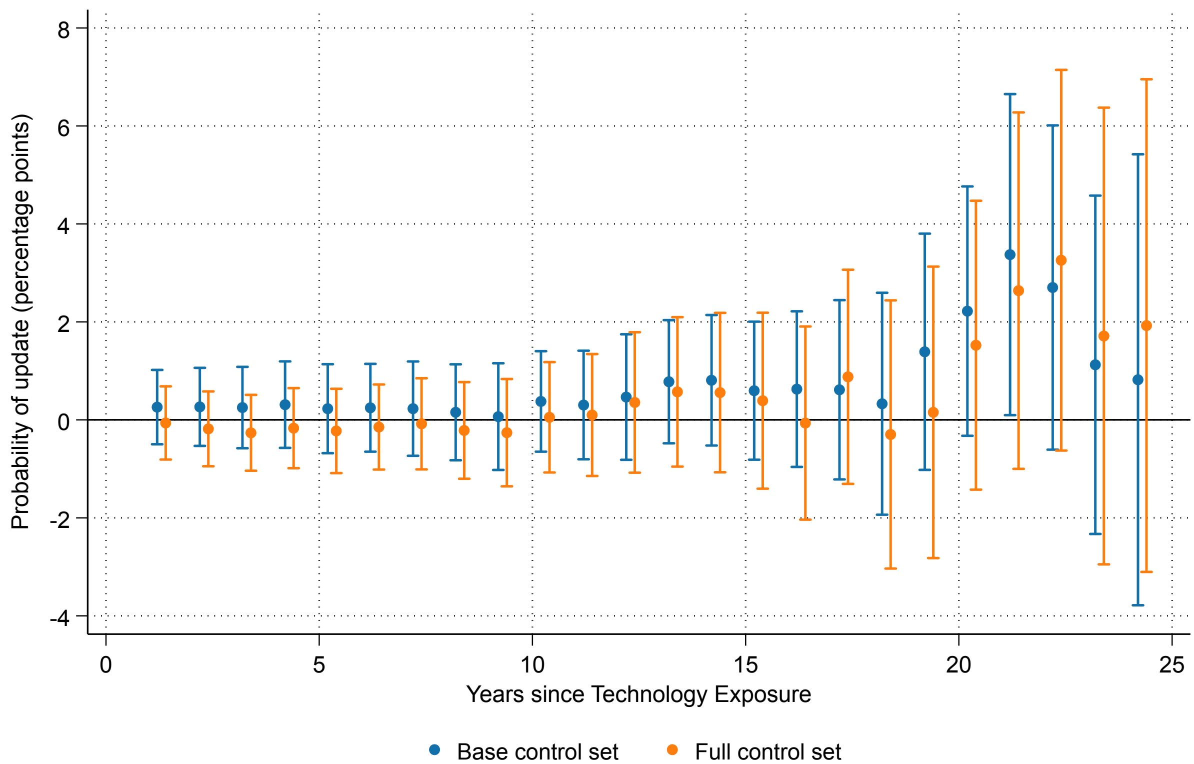


Figure presents estimates of equation (3). The dependent variable is a dummy for the curriculum being updated (conditional on not having being updated yet). Coefficients multiplied by 100. Standard errors clusted by occupation, whiskers represent 95% confidence intervals.

Figure 13: Changes in Digital Technology and Social Skill Use in Updated Curricula, 1976–2021

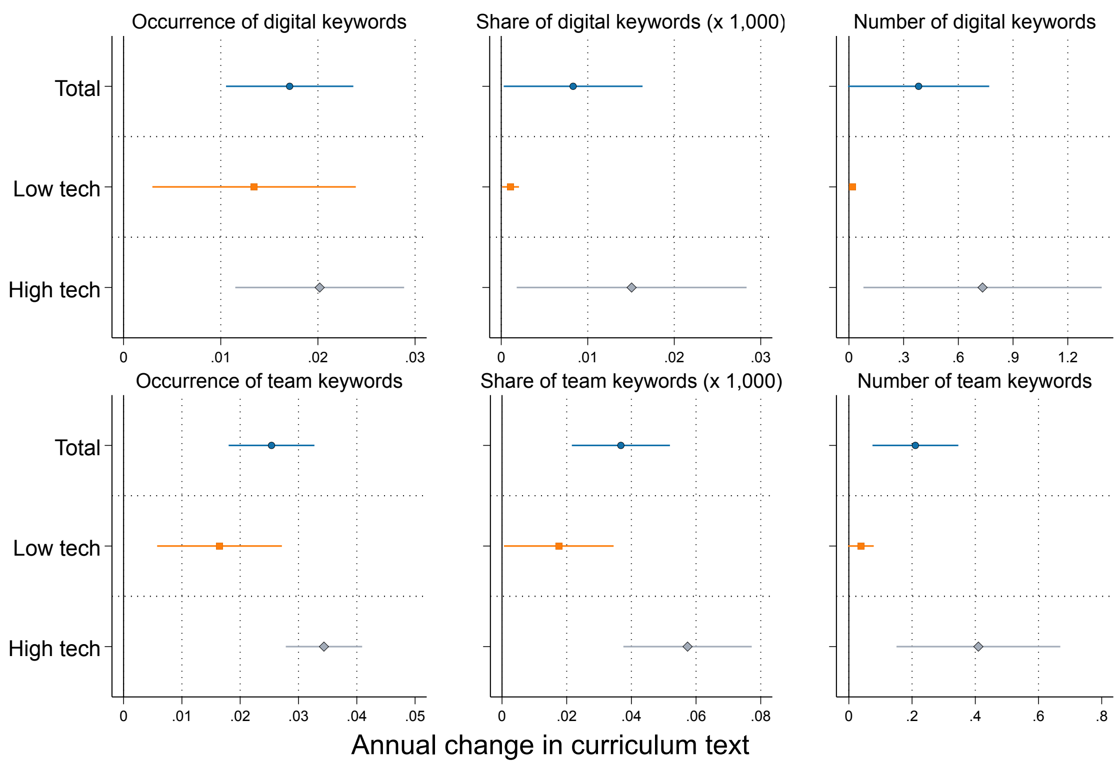


Figure reports coefficients on a linear timetrend, from a regression of keyword occurrence, keyword shares, or keyword counts in vocational training curricula (see equation (4)), for the subsample of curricula with updates over 1976–2021. High tech (low tech) defined as curricula with an initial digital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

Figure 14: Changes in Routine Task Intensity in Updated Curricula, 1976–2021

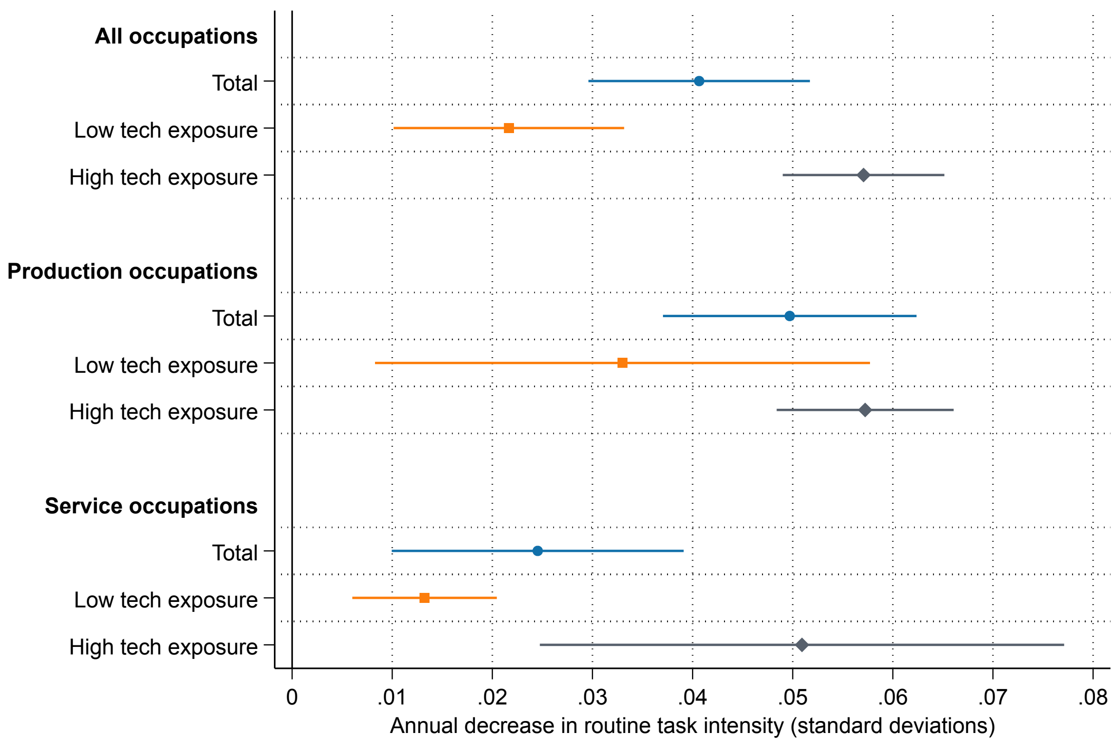
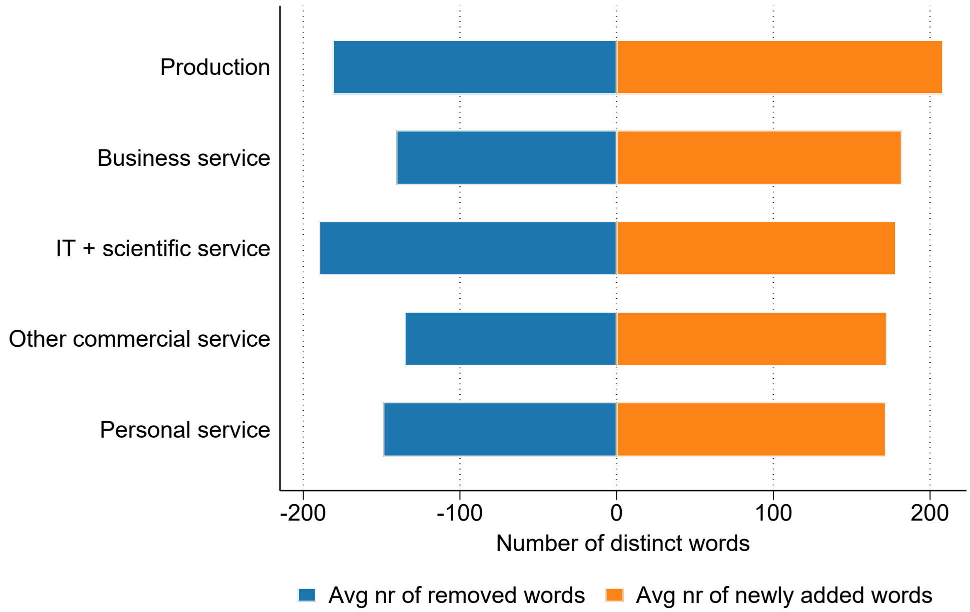


Figure reports coefficients on a linear timetrend, from a regression of routine task content in vocational training curricula (see equation (4)), for the subsample of curricula with updates over 1976–2021. Horizontal lines reflect 95% confidence intervals. High tech (low tech) defined as curricula with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

Figure 15: Removed and Newly Added Words in Curriculum Updates

A. Absolute word counts



B. As a share of prior curriculum word count

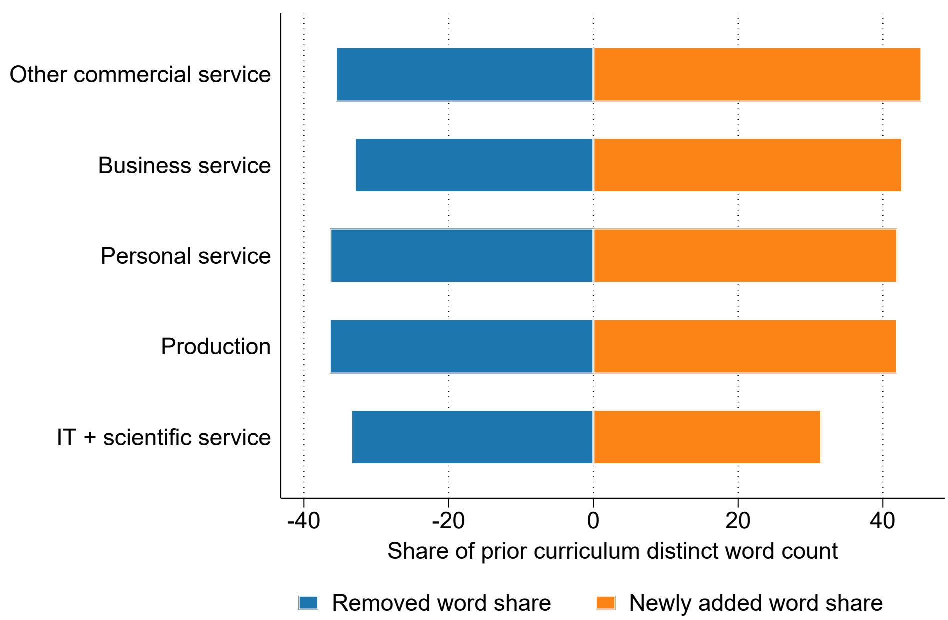
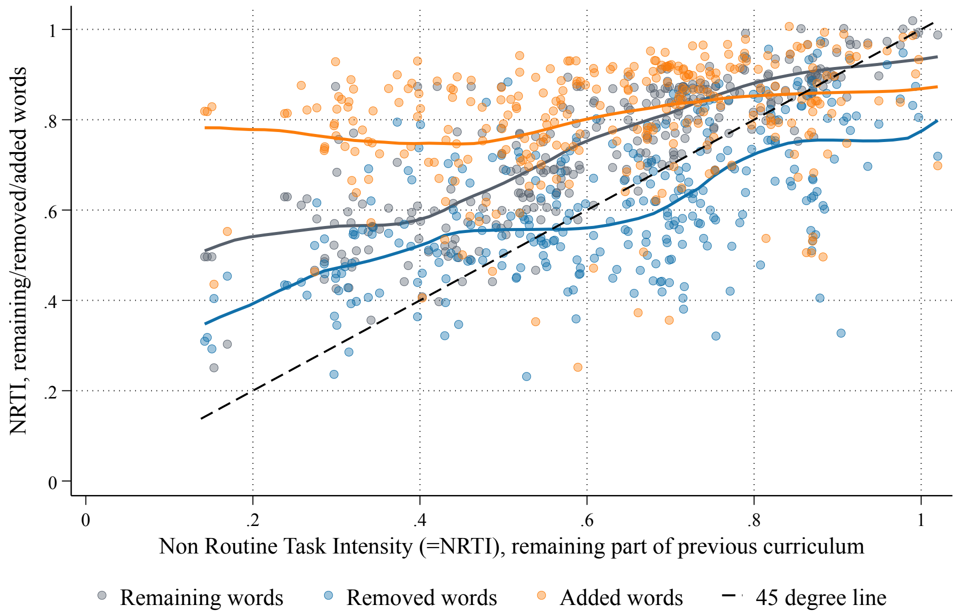


Figure presents the average number of distinct removed and distinct newly added words across curriculum updates in absolute number (panel A) and as a share of distinct prior curriculum word counts (panel B), by broad occupation.

Figure 16: Changes in Skill Content from Removed, Remaining, and Newly Added Words

A. Non-routine task intensity



B. Word complexity

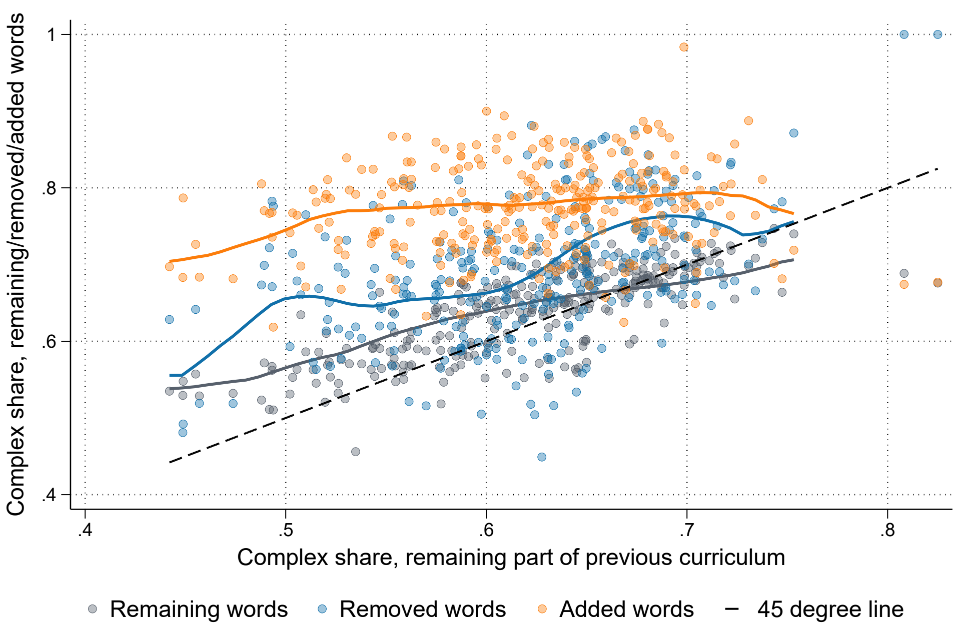


Figure presents the non-routine task intensity (panel A) and complexity (panel B) of new curriculum words plotted against remaining words in the previous curriculum. Fitted lines are local polynomials weighted by training occupation employment shares.

Figure 17: Wage Impacts of Curriculum Updates

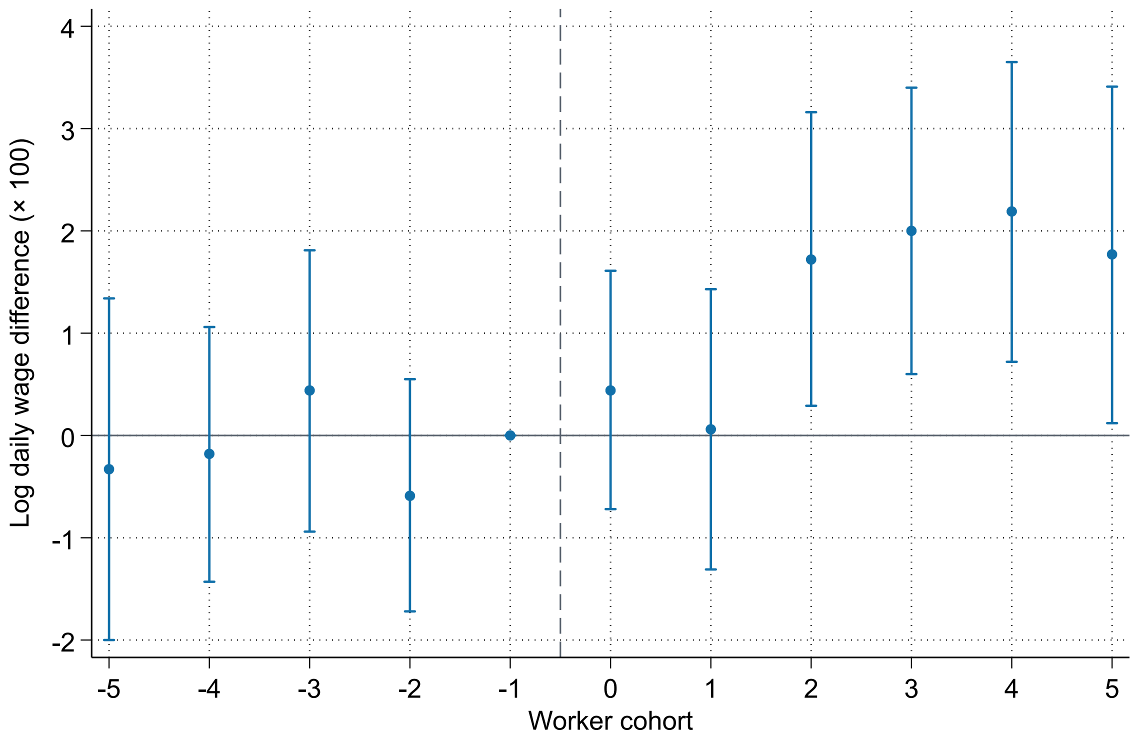
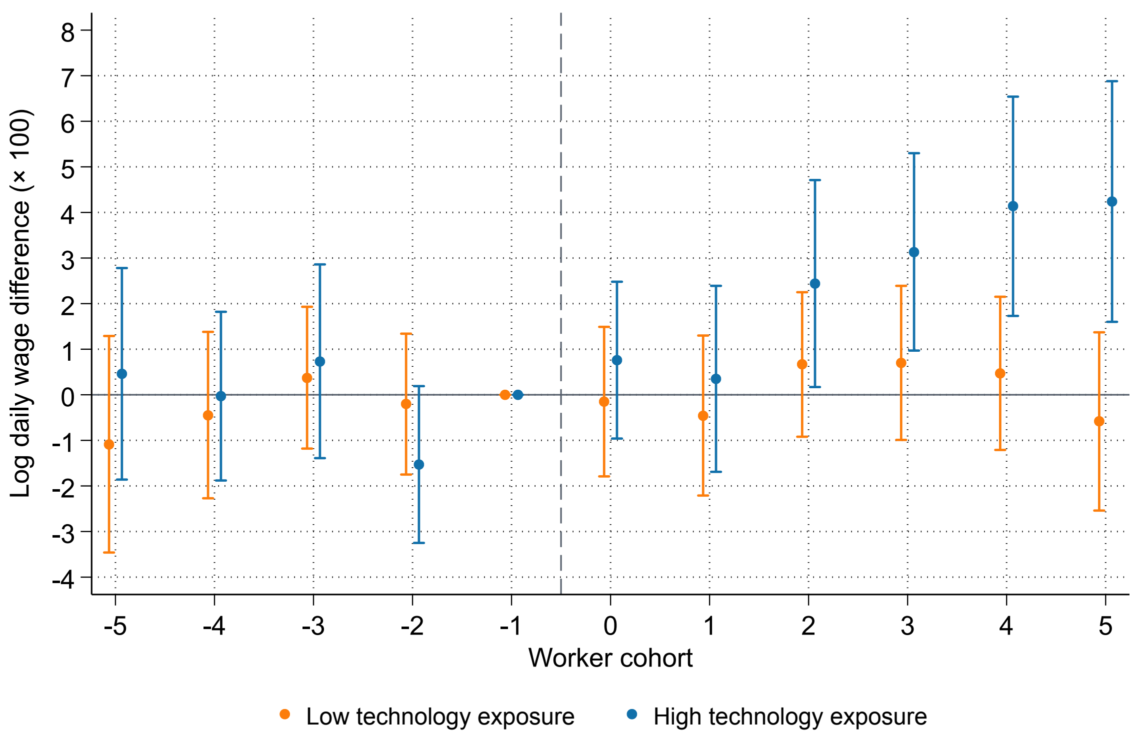


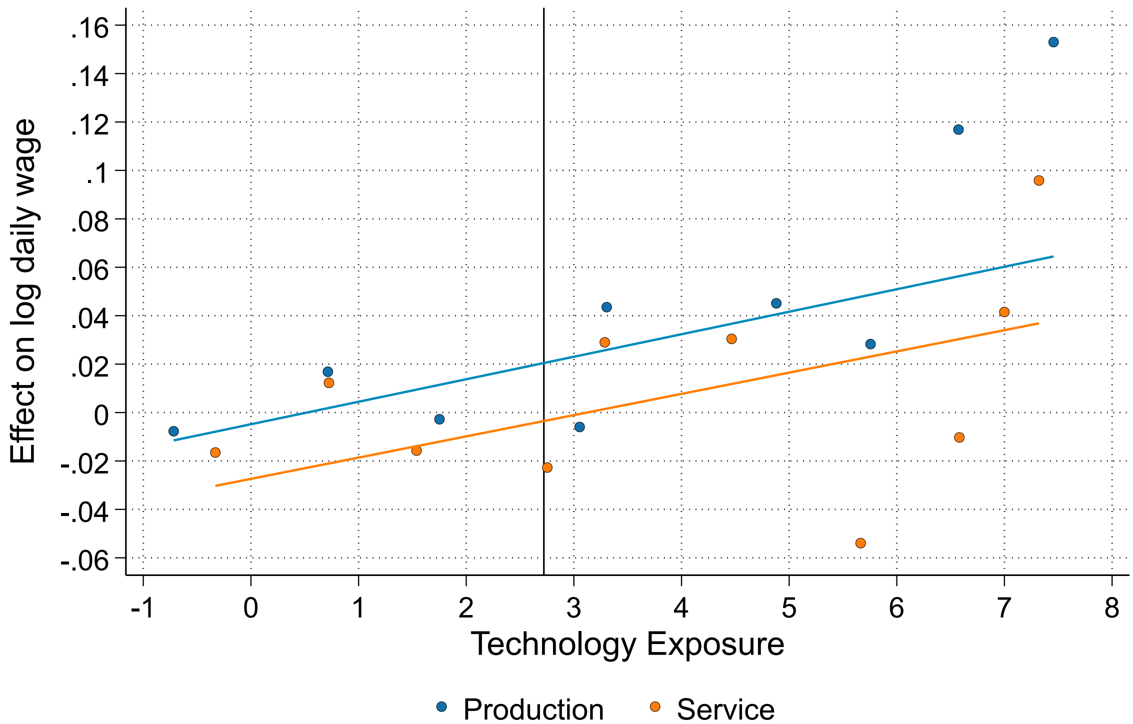
Figure reports stacked difference-in-differences estimates of equation (5), and 95% confidence intervals. Cohort 0 is the first cohort with the new curriculum; cohort -1 is the reference category. Individuals are included up to five years after graduation. Standard errors clustered at the level of training occupation by event.

Figure 18: 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 training occupation by event.

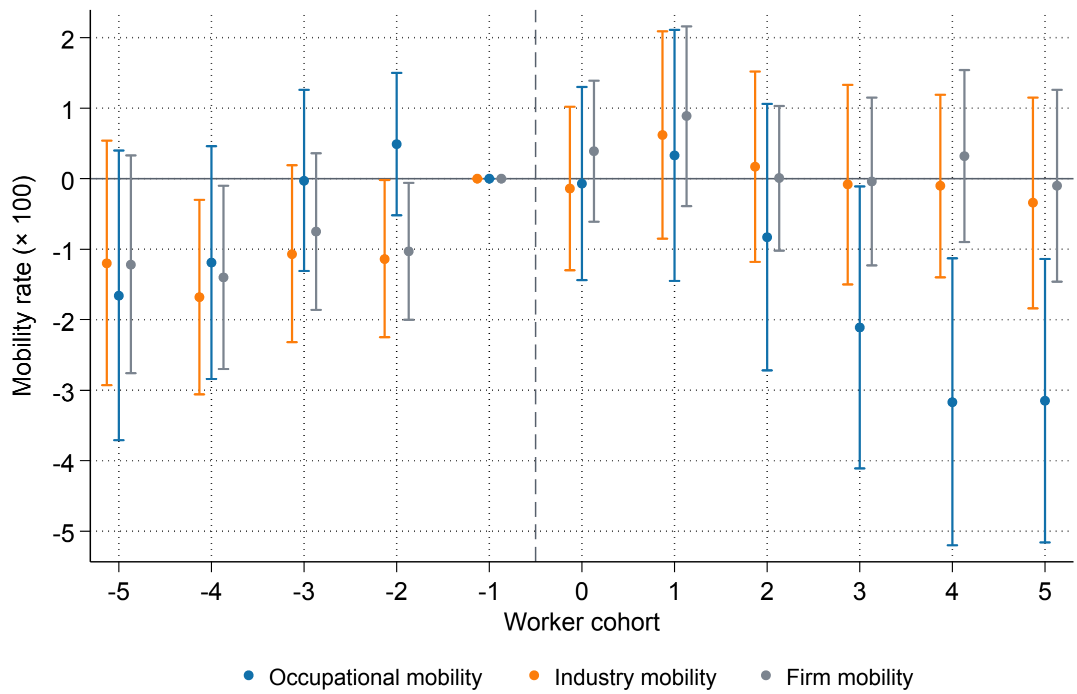
Figure 19: Update-Specific Wage Impacts by Curriculum Technology Exposure



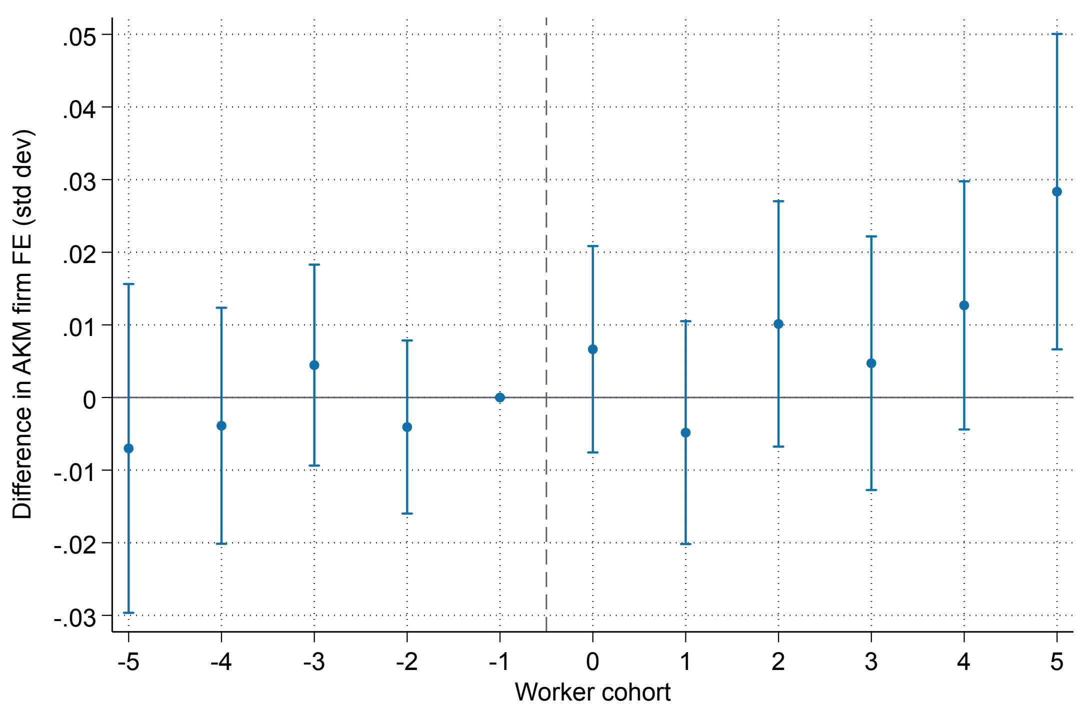
Binscatter of wage returns estimated separately for each curriculum update event, against curriculum technology exposure, measured as the log of linked patents. The vertical line indicates median technology exposure as used throughout the paper.

Figure 20: Worker Mobility Impacts of Curriculum Updates

A. Occupation, industry, and firm mobility



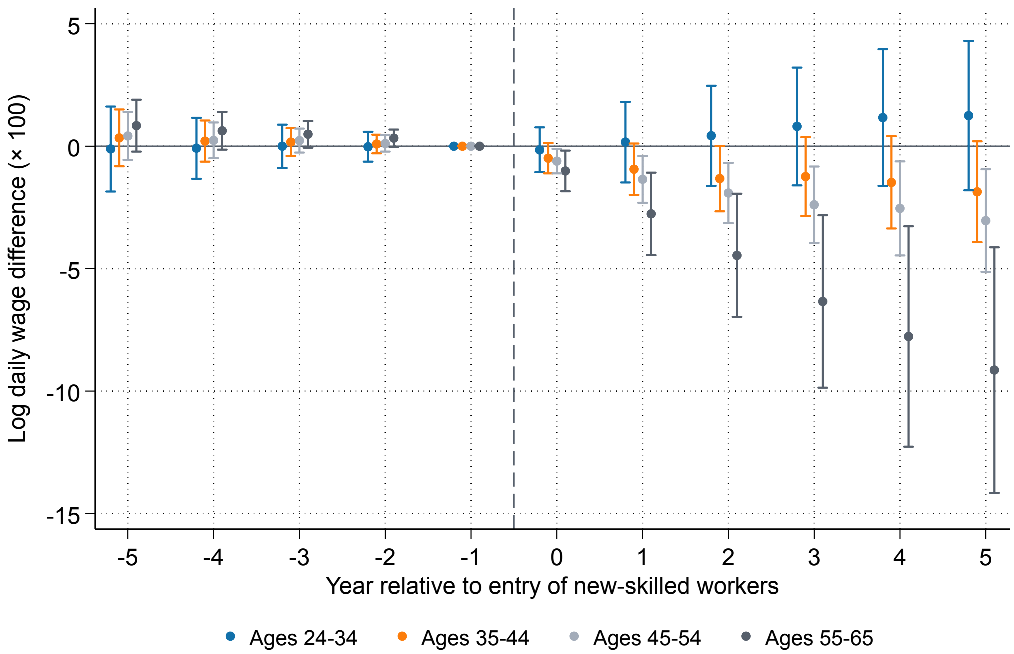
B. Firm AKM fixed effects



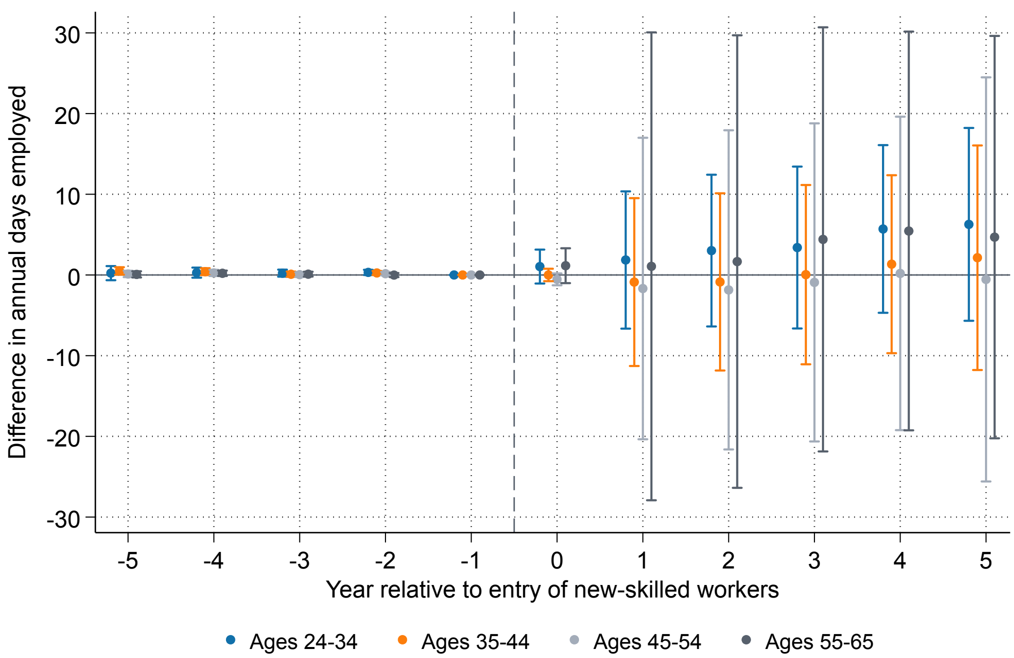
Stacked difference-in-differences estimates of equation (5), and 95% confidence intervals. Mobility is defined relative to the apprenticeship position in panel A. Cohort 0 is the first cohort with the new curriculum; cohort -1 is the reference category. Individuals are included up to five years after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

Figure 21: Wage and Employment Impacts of Curriculum Updates for Occupational Incumbents

A. Log daily wage

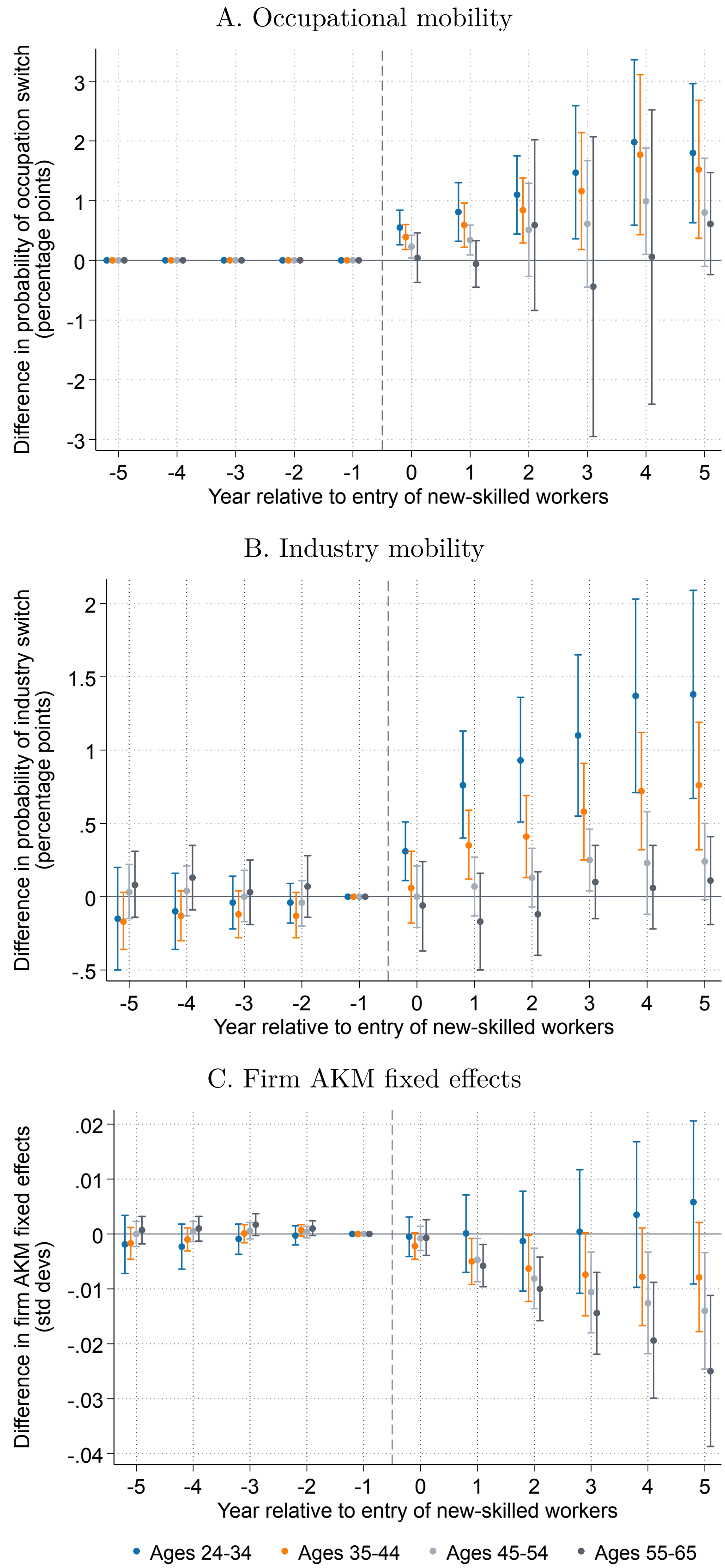


B. Annual days of employment



Stacked difference-in-differences estimates of equation (6), and 95% confidence intervals. Based on 339 curriculum update events.

Figure 22: Job Mobility Impacts of Curriculum Updates for Occupational Incumbents

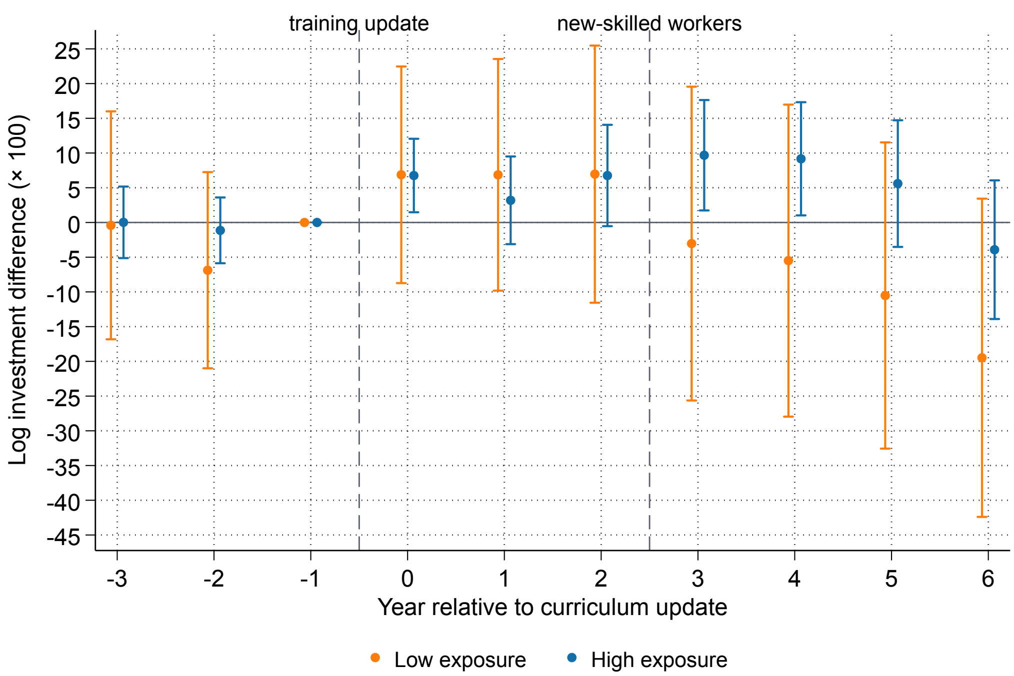


Stacked difference-in-differences estimates of equation (6), and 95% confidence intervals. Based on 339 curriculum update events.

Figure 23: 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 209 curriculum update 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	11.2	-6.0	100.9
Occupations in warehousing and logistics	4.3	0.1	82.3
Occupations in machine-building and -operating	3.5	-1.4	136.0
Sales occupations in retail trade	3.5	-2.5	70.0
Professional drivers (cargo trucks)	3.3	-0.8	87.7
Technical occupations in automotive industries	2.9	-1.5	99.3
Bankers	2.1	-0.4	140.4
Occupations in electrical engineering	2.0	-1.1	151.9
Management assistants in wholesale and foreign trade	1.5	-0.9	120.8
Occupations in metal constructing	1.4	-0.4	95.5

Source: SIAB. Average employment share: Average share of occupational regular full-time employment in total regular full-time employment across the years 1975–2017. Δ Employment share: Change in the share of occupational regular full-time employment in total regular full-time employment between 1975 and 2017 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	0.122	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 | update = 1†	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
Examples of Most Updated Training Occupations		
Flexograph	Production	0.12
Electronics technician for automation technology	Production	0.10
Industrial mechanic	Production	0.10
Retail clerk	Business service	0.09
Electrician	Production	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
Examples of Least Updated Training Occupations		
Gardener	Production	0.02
Manufactured porcelain painter	Production	0.02
Civil engineer	Production	0.01
Foundation engineering specialist	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
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
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
Cutting machine operator	Production
Electronics technician for information and system technology	Production
Electronics technician for building and infrastructure systems	Production
Plant mechanic	Production
Tool mechanic	Production
Electronics technician for automation technology	Production
10 Least Exposed Training Occupations	
Plant technologist	Production
Factory fireman	Business service
Leather production and tanning technology specialist	Production
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.

Table 5: Curriculum Updates and Digital Technology Exposure

	A. Unweighted			
	(1)	(2)	(3)	(4)
Digital Tech Exposure	0.42***	0.46***	0.50***	0.48***
	(0.09)	(0.10)	(0.11)	(0.10)
N	10,729	10,729	10,729	10,729
	B. Weighted by initial employment share			
	(5)	(6)	(7)	(8)
Digital Tech Exposure	0.84***	0.80***	0.81***	0.83***
	(0.17)	(0.17)	(0.16)	(0.15)
N	10,729	10,729	10,729	10,729
Initial Curriculum Year FE	X	X	X	X
Year FE	X	X	X	X
Broad Occ FE		X	X	X
Broad Occ FE × Year FE			X	X
Initial Empl. Share				X

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

Table 6: Years until Curriculum Updates and Digital Technology Exposure

	A. Unweighted		
	(1)	(2)	(3)
Digital Tech Exposure	-0.45^{**}	-0.62^{**}	-0.63^{**}
	(0.17)	(0.19)	(0.19)
N	376	376	376
	B. Weighted by initial employment		
	(4)	(5)	(6)
Digital Tech Exposure	-0.53^{*}	-0.68^{**}	-0.73^{***}
	(0.23)	(0.24)	(0.21)
N	376	376	376
Initial Curriculum Year FE	X	X	X
Broad Occ FE		X	X
Initial Empl. Share			X

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

Table 7: Type of Curriculum Update and Digital Technology Exposure

	A. Content update only				B. Content update + Renaming			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Digital Tech Exposure	0.21^{**}	0.22^{***}	0.26^{***}	0.26^{***}	0.20^{*}	0.23^{**}	0.23^{**}	0.22^{*}
	(0.07)	(0.06)	(0.07)	(0.07)	(0.08)	(0.08)	(0.09)	(0.09)
N	10,546	10,546	10,546	10,546	10,499	10,499	10,499	10,499
	C. Content update + Aggregation				D. Content update + Segregation			
	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)
Digital Tech Exposure	0.22^{**}	0.23^{**}	0.21^{*}	0.19^{*}	0.07^{*}	0.08^{*}	0.08^{*}	0.07^{*}
	(0.08)	(0.09)	(0.09)	(0.09)	(0.03)	(0.03)	(0.03)	(0.03)
N	10,449	10,449	10,449	10,449	10,368	10,368	10,368	10,368
Initial Curriculum Year FE	X	X	X	X	X	X	X	X
Year FE	X	X	X	X	X	X	X	X
Broad Occ FE		X	X	X		X	X	X
Broad Occ FE × Year FE			X	X			X	X
Initial Empl. Share				X				X

Dependent variable: Dummy for curriculum update type. Linear probability models, unweighted, coefficients multiplied by 100. Initial Curriculum Year FE in five year bins. Standard errors clustered at the 5 digit occupation level. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. Based on the yearly panel. The reference group is always “no change”. The categories are not mutually exclusive and the sum of the number of segregations, aggregations and pure content changes is larger than the overall number of changes.

Table 8: Descriptives of Vocationally Trained Labor Market Entrants

	Mean (1)	SD (2)	Median (3)	N (4)
Age	23.28	3.02	23.00	3,286,091
Year of birth	1975	9.61	1975	3,286,091
Female	0.40	0.49	0.00	3,286,091
Daily wage	70.42	29.69	71.67	2,350,192
Annual daily wage growth	0.33	6.96	0.06	3,043,054
Years of training	2.82	0.53	2.88	3,286,091
Typical years of training	3.00	0.38	3.00	3,286,091
Annual days employed	268.42	138.28	365.00	3,286,091
Annual labor earnings	18,359	13,620	18,554	3,286,091
Firm size	559.37	2751.89	40.00	2,796,232
Job mobility, relative to apprenticeship:				
Occupation	0.35	0.48	0.00	3,286,091
Industry	0.40	0.49	0.00	3,286,091
Firm	0.58	0.49	1.00	3,286,091
Job mobility, year-to-year:				
Occupation	0.16	0.37	0.00	3,286,091
Industry	0.17	0.38	0.00	3,286,091
Firm	0.26	0.44	0.00	3,286,091

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 are worker by year observations.

Table 9: Descriptives of Stacked, Matched Firm Sample

	Treated		Control	
	Mean (1)	SD (2)	Mean (3)	SD (4)
Number of workers	389	1521	243	530
Log(investments)	6.00	2.58	5.84	2.43
Any investment (1/0)	0.78	0.41	0.78	0.41
Manufacturing sector (1/0)	0.58	0.49	0.22	0.41
N unique firms	3,360		3,636	

Source: LIAB. For year $t = -1$.

Appendix

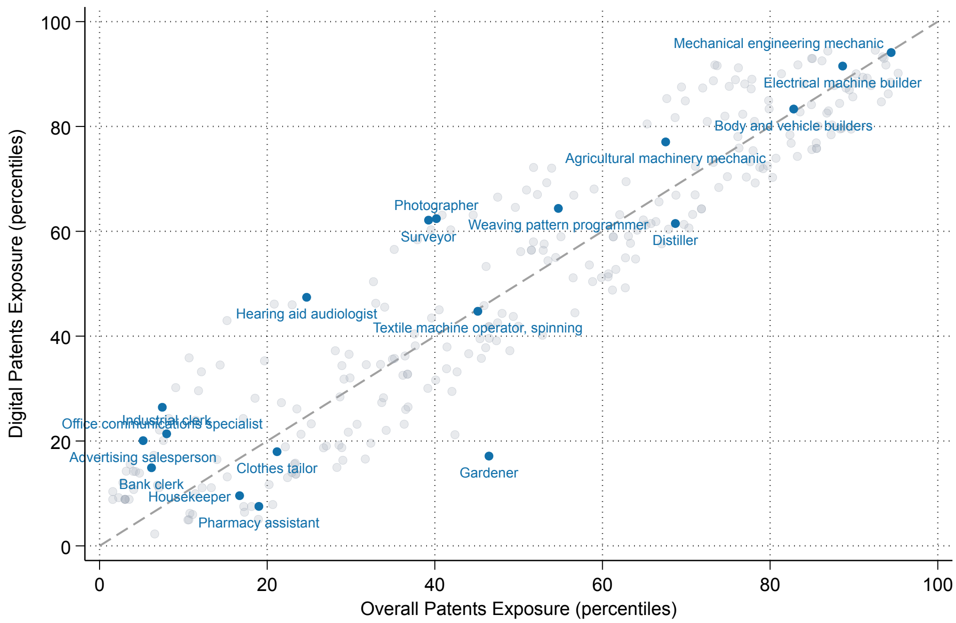
Table of Contents

A Appendix figures

A.1 Data and measurement

Figure A1: Digital and Overall Technology Exposure of Training Curricula

A. Average over 1971–1997



B. Average over 1998–2021

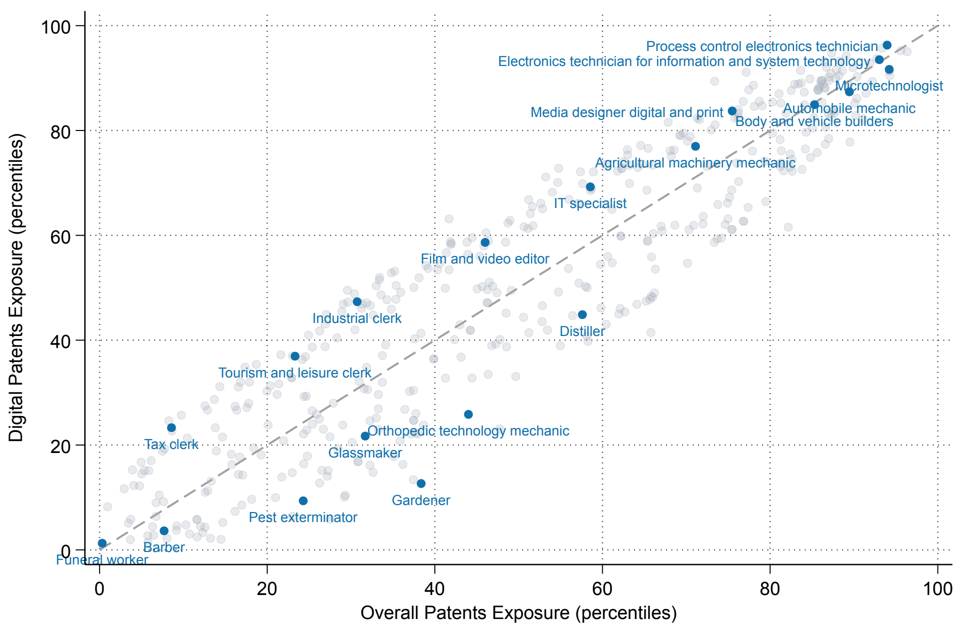
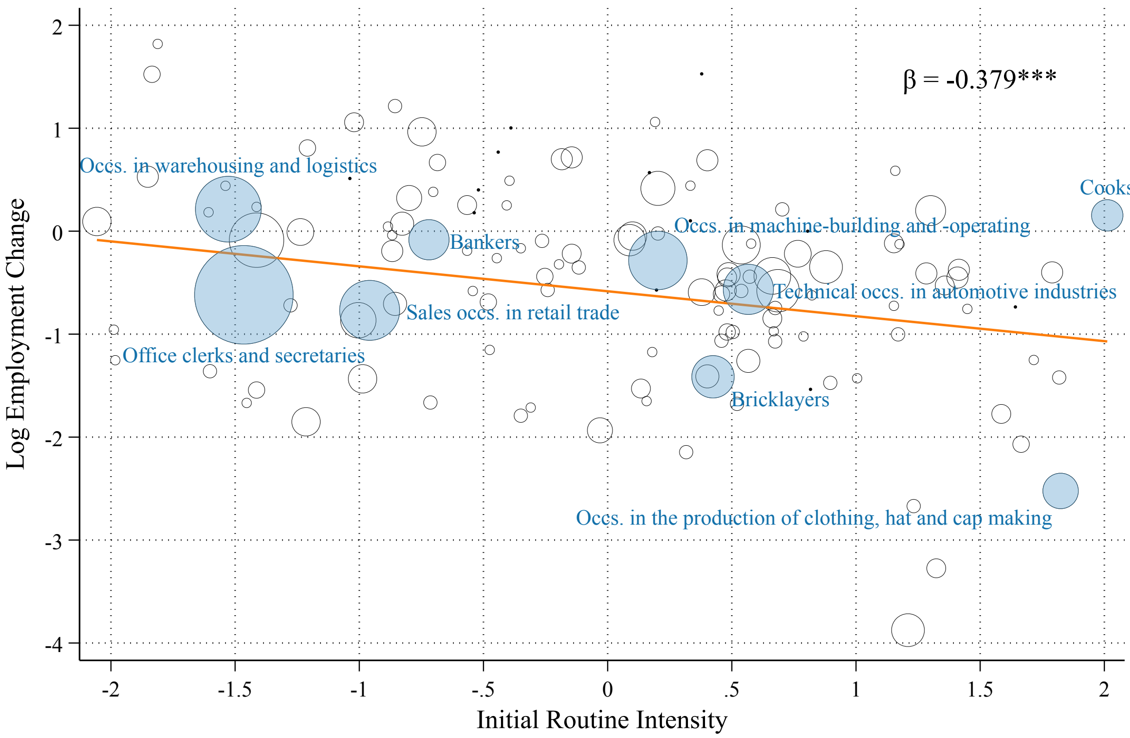


Figure presents a scatter plot of the relationship between occupational exposure to overall and digital patents for 1971–1996 (panel A) and 1997–2021 (panel B). Each point corresponds to the average percentile of overall ($x-$axis) and digital ($y-$axis) exposure of one occupational curriculum, where 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 A2: 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 A3: Curriculum Survival Rates by Technology Exposure

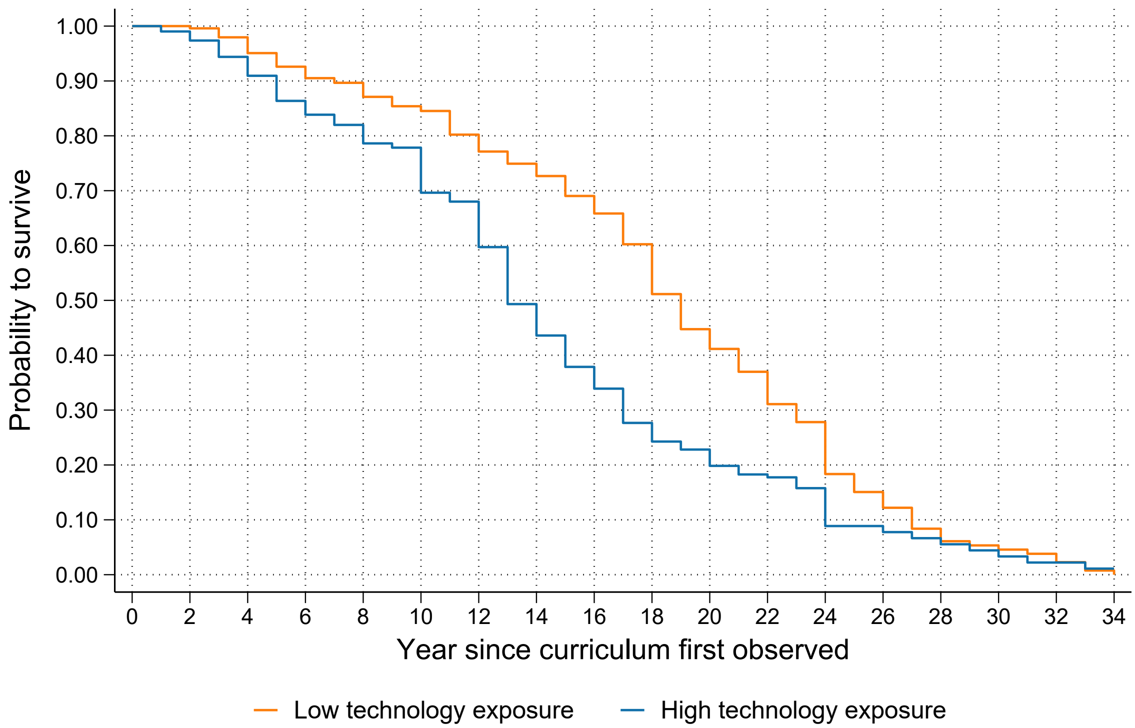


Figure shows Kaplan-Meier survival curves for all curricula updated at some point over the 1970–2021 period, separately by technology exposure.

Figure A4: Changes in Digital Technology and Social Skill Use in All Curricula, 1976–2021

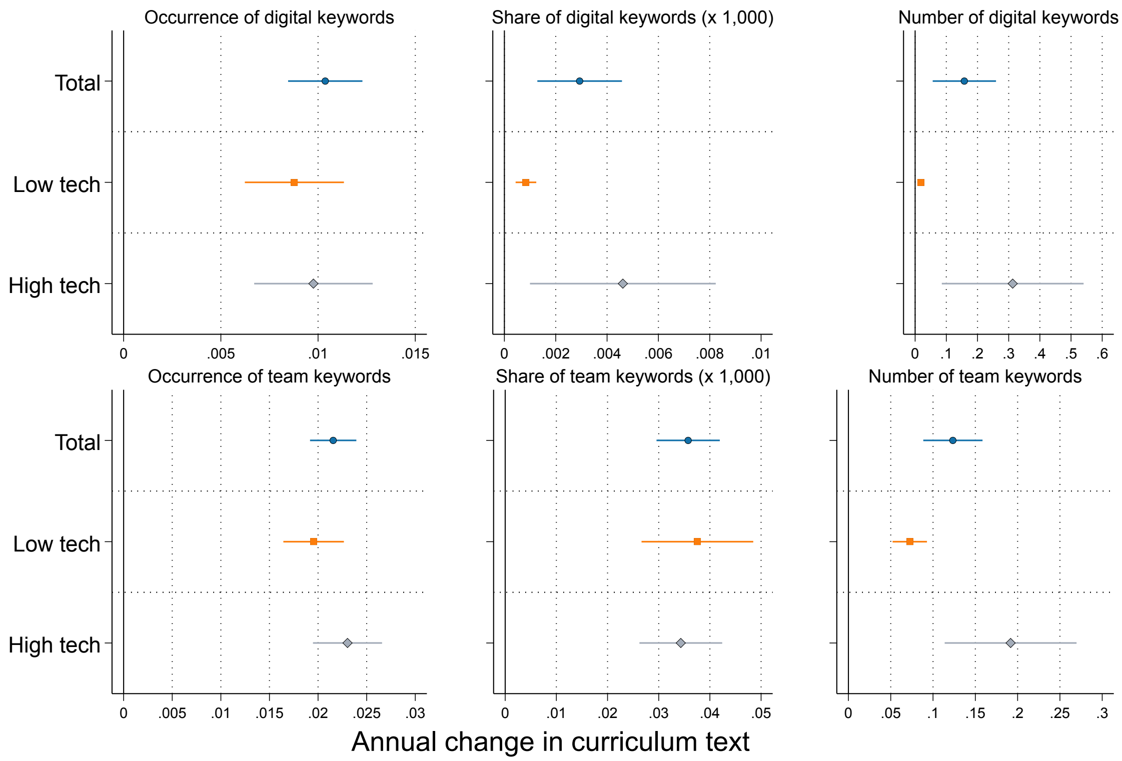


Figure reports coefficients on a linear timetrend, from a regression of keyword occurrence, keyword shares, or keyword counts in vocational training curricula (see equation (4)), for all curricula over 1976–2021. High tech (low tech) defined as curricula with an initial digital technology exposure above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

Figure A5: Changes in Routine Task Intensity in All Curricula, 1976–2021

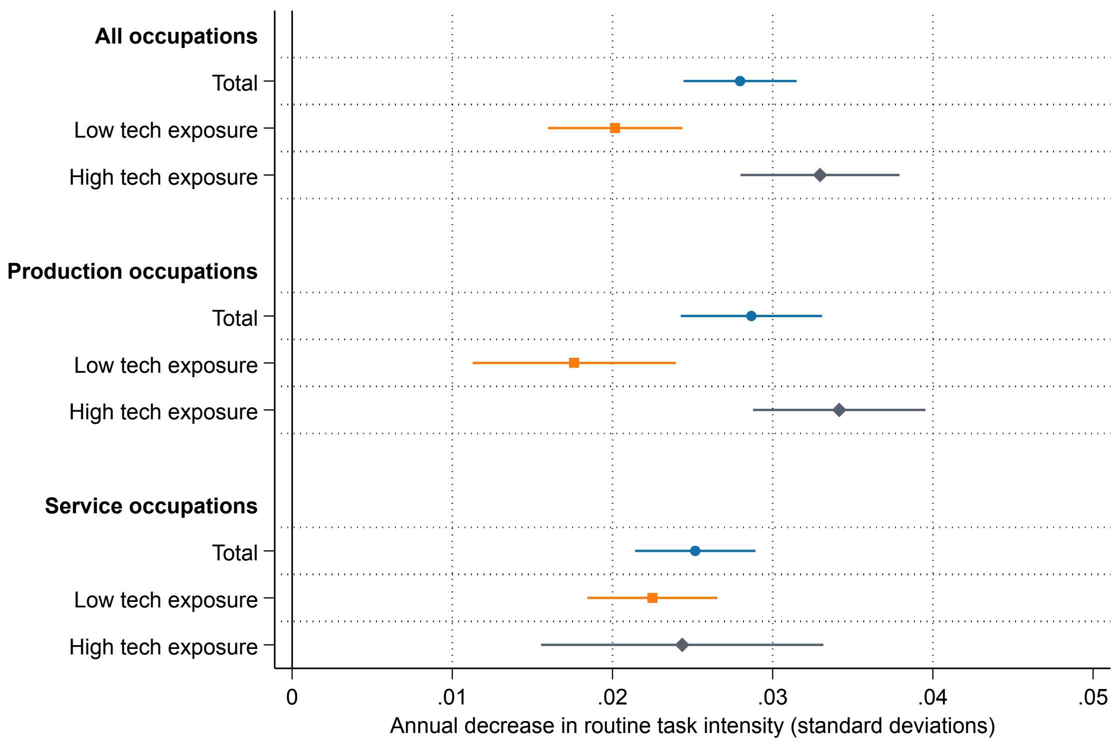


Figure reports coefficients on a linear timetrend, from a regression of routine task content in vocational training curricula (see equation (4)), for all curricula over 1976–2021. Horizontal lines reflect 95% confidence intervals. High tech (low tech) defined as curricula with an initial digital technology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

Figure A6: Changes in Word Complexity in Updated Curricula, 1976–2021

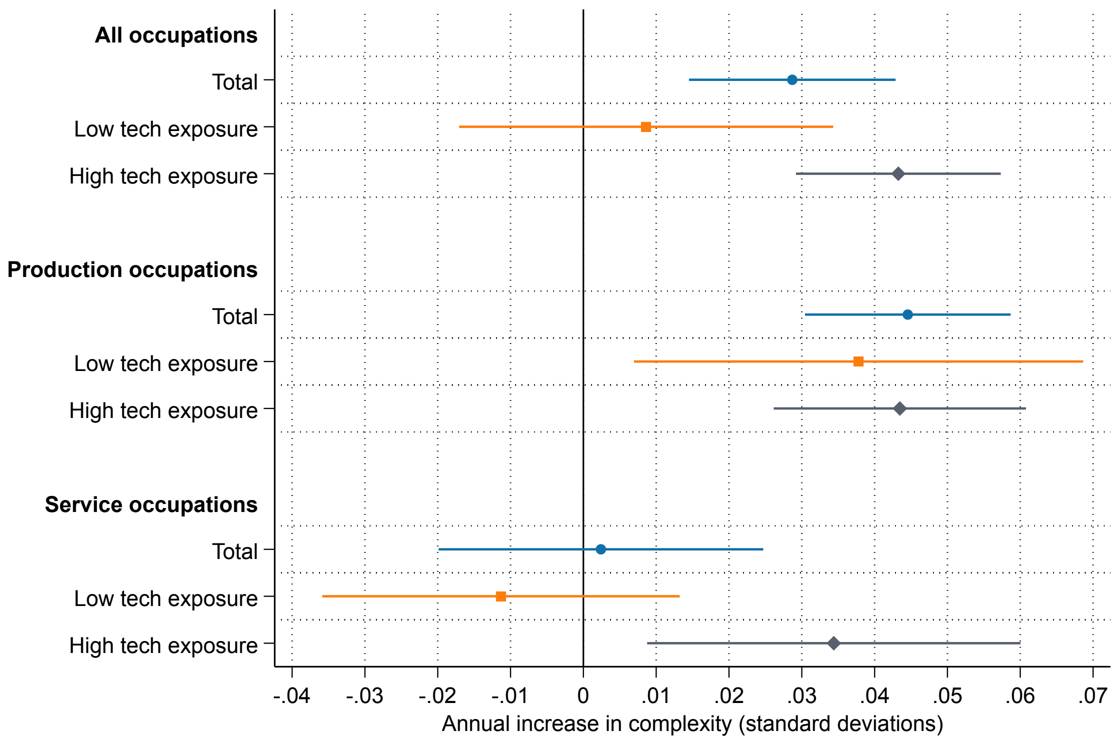


Figure reports coefficients on a linear timetrend, from a regression of complex word shares in vocational training curricula (see equation (4)), for all curricula over 1976–2021. Complex words are defined as those not in the Dale and Chall (1948) list, following Autor and Thompson (2024). High tech (low tech) defined as curricula with an initial digital technology exposure above (at or below) the median across all occupations.

Figure A7: Removed and Added Word Shares Across Training Occupations

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

A.3 Labor market impacts

Figure A8: Impacts of Curriculum Updates on Training Firm Composition

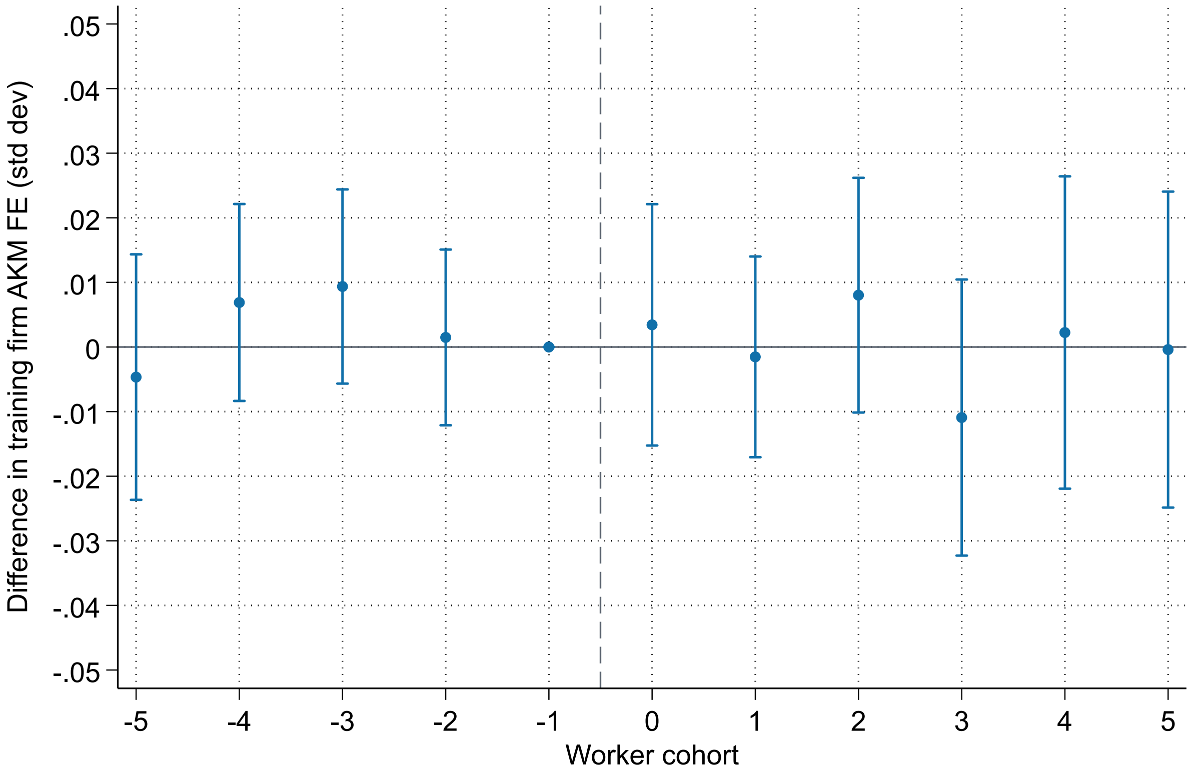


Figure reports stacked difference-in-differences estimates of equation (5), and 95% confidence intervals; estimated separately by year post training. Cohort 0 is the first cohort with the new curriculum; cohort -1 is the reference category. Standard errors clustered at the level of training occupation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

Figure A9: Predicted Log Daily Wages for Treated and Control Group Workers

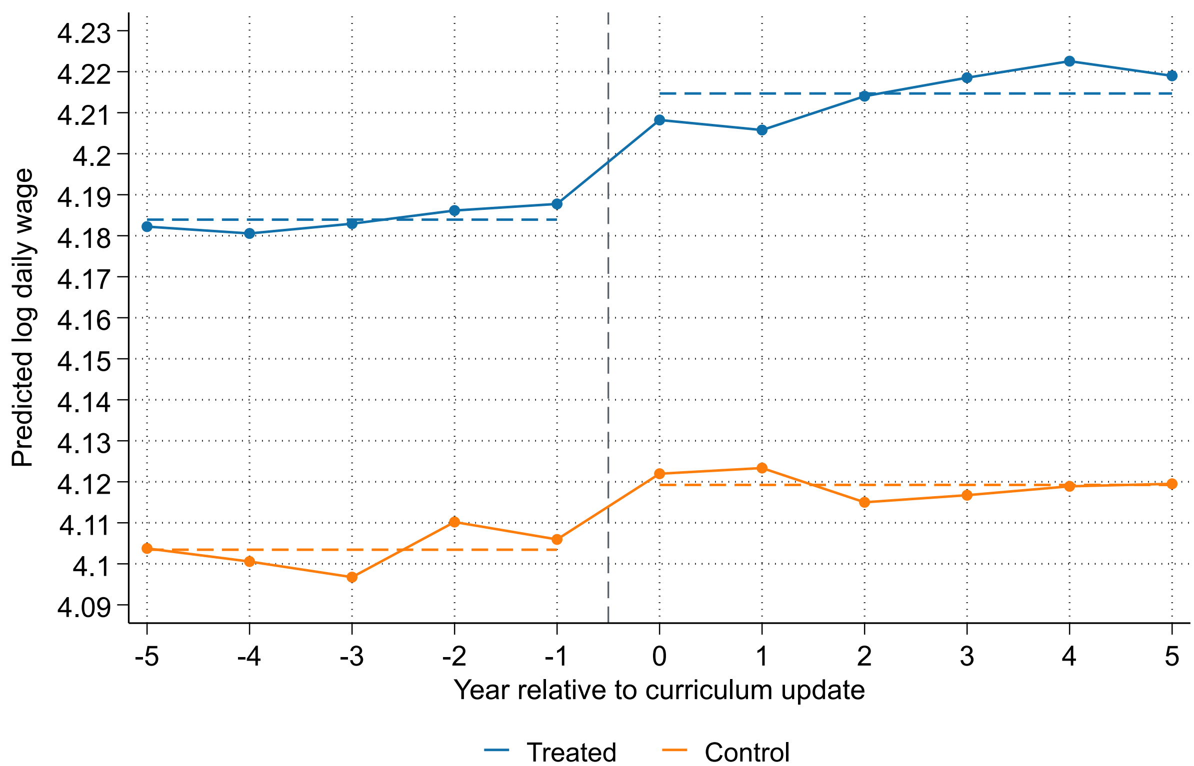
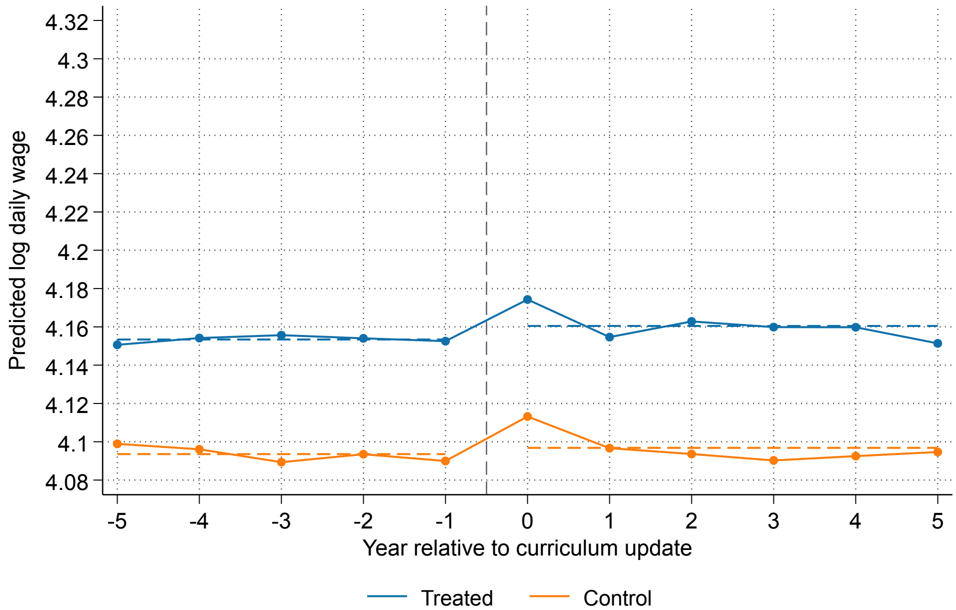


Figure reports predicted log wages for treated and control group workers using the stacked difference-in-differences estimate of equation (5). Dashed lines indicate means of pre- and post-treatment predictions.

Figure A10: Predicted Log Daily Wages for Treated and Control Group Workers

A. Low technology exposure



B. High technology exposure

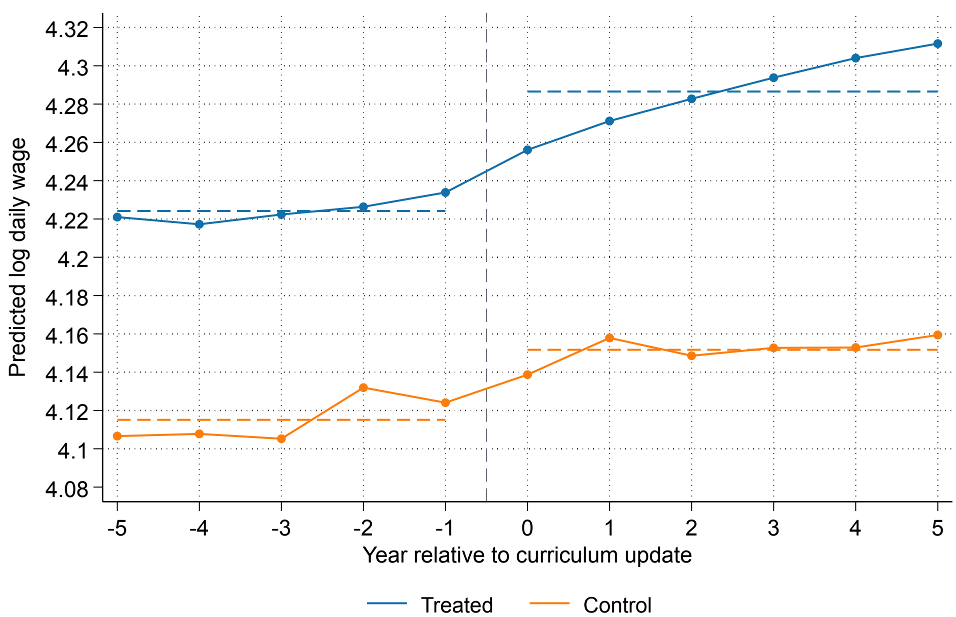
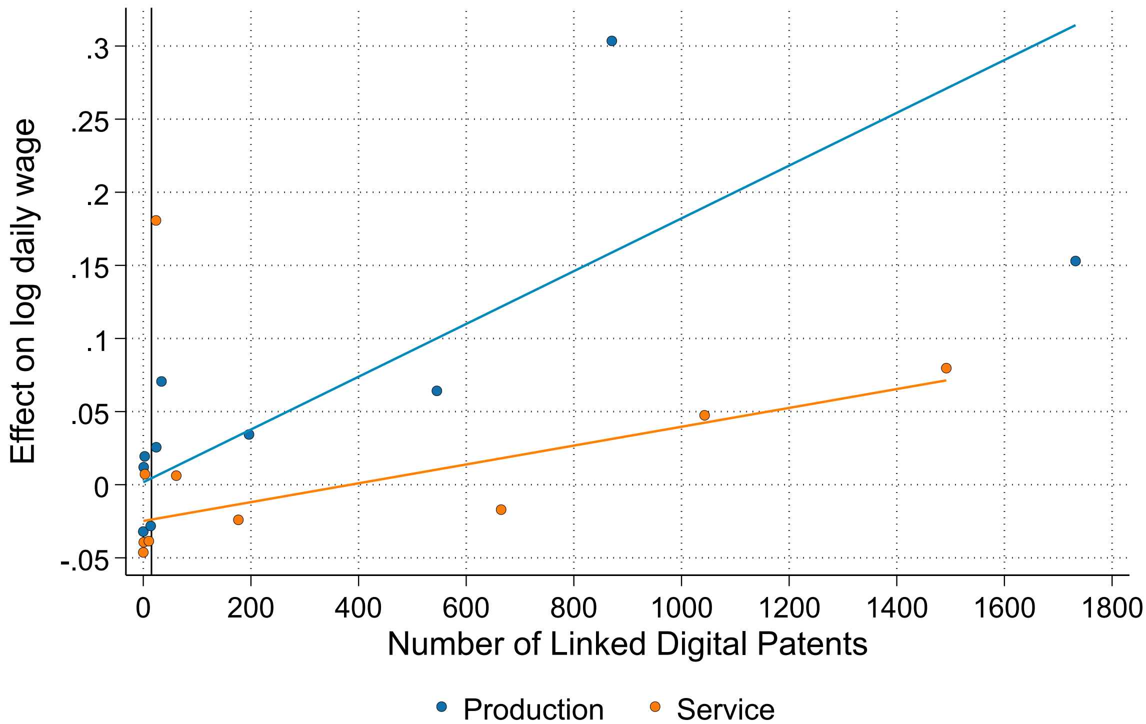


Figure reports predicted log wages for treated and control group workers using the stacked difference-in-differences estimate of equation (5). Dashed lines indicate means of pre- and post-treatment predictions.

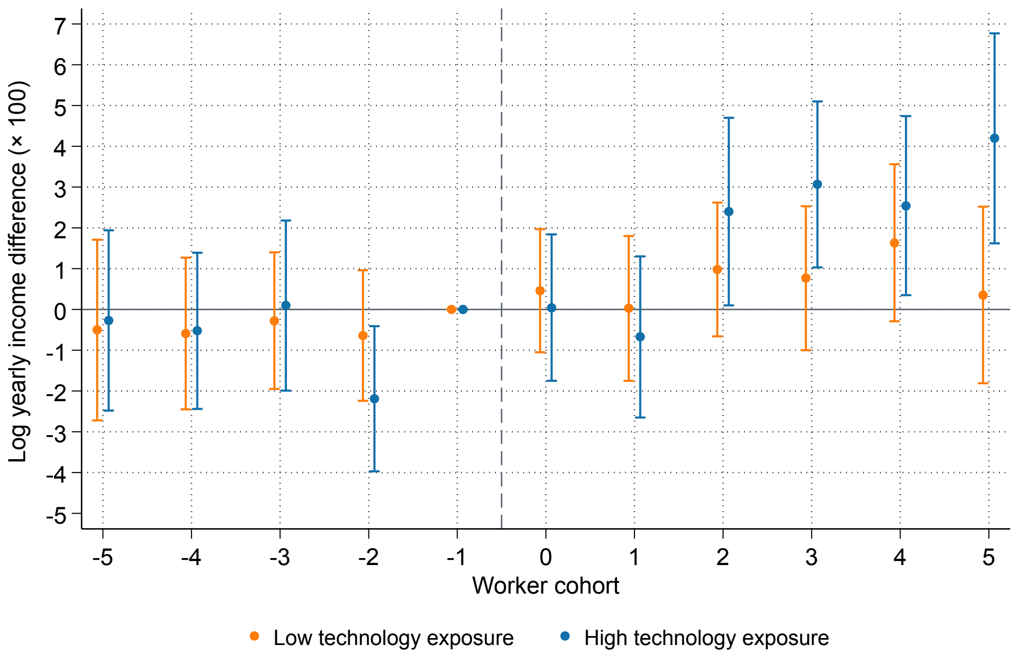
Figure A11: Update-Specific Wage Impacts by Curriculum Technology Exposure



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 A12: Impact of Curriculum Updates on Annual Income and Annual Days Employed

A. Log annual income by technology exposure



B. Annual days employed by technology exposure

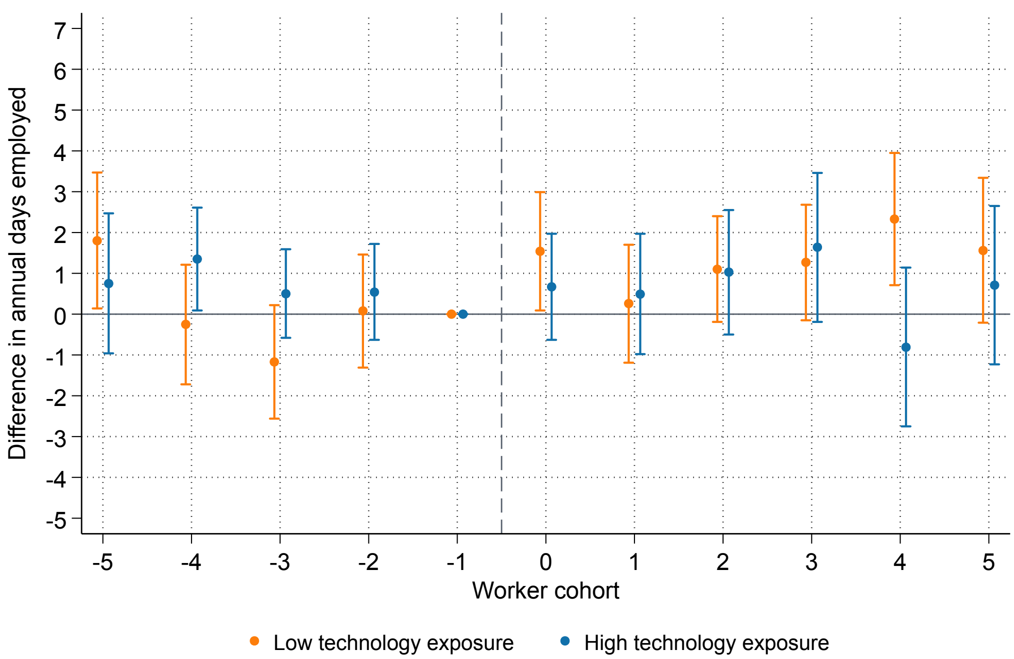


Figure reports stacked difference-in-differences estimates of equation (5), and 95% confidence intervals. Cohort 0 is the first cohort with the new curriculum; cohort -1 is the reference category. Individuals are included up to five years after graduation. Standard errors clustered at the level of training occupation by event.

Figure A13: Log Daily Wage Impacts of Curriculum Updates By Experience

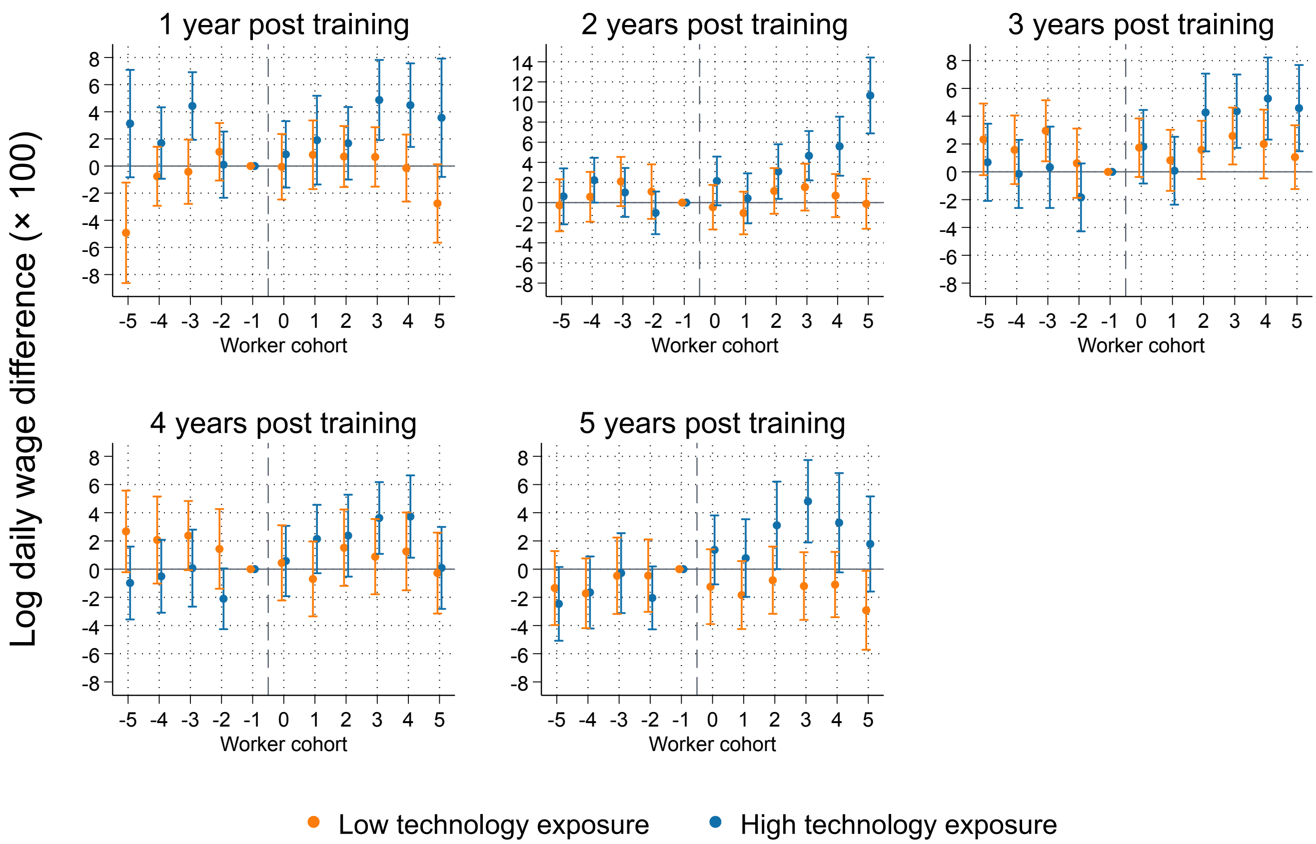


Figure reports stacked difference-in-differences estimates of equation (5), and 95% confidence intervals; estimated separately by year post training. Cohort 0 is the first cohort with the new curriculum; cohort -1 is the reference category. Standard errors clustered at the level of training occupation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

Figure A14: Impacts of Curriculum Updates on Later Educational Upgrading

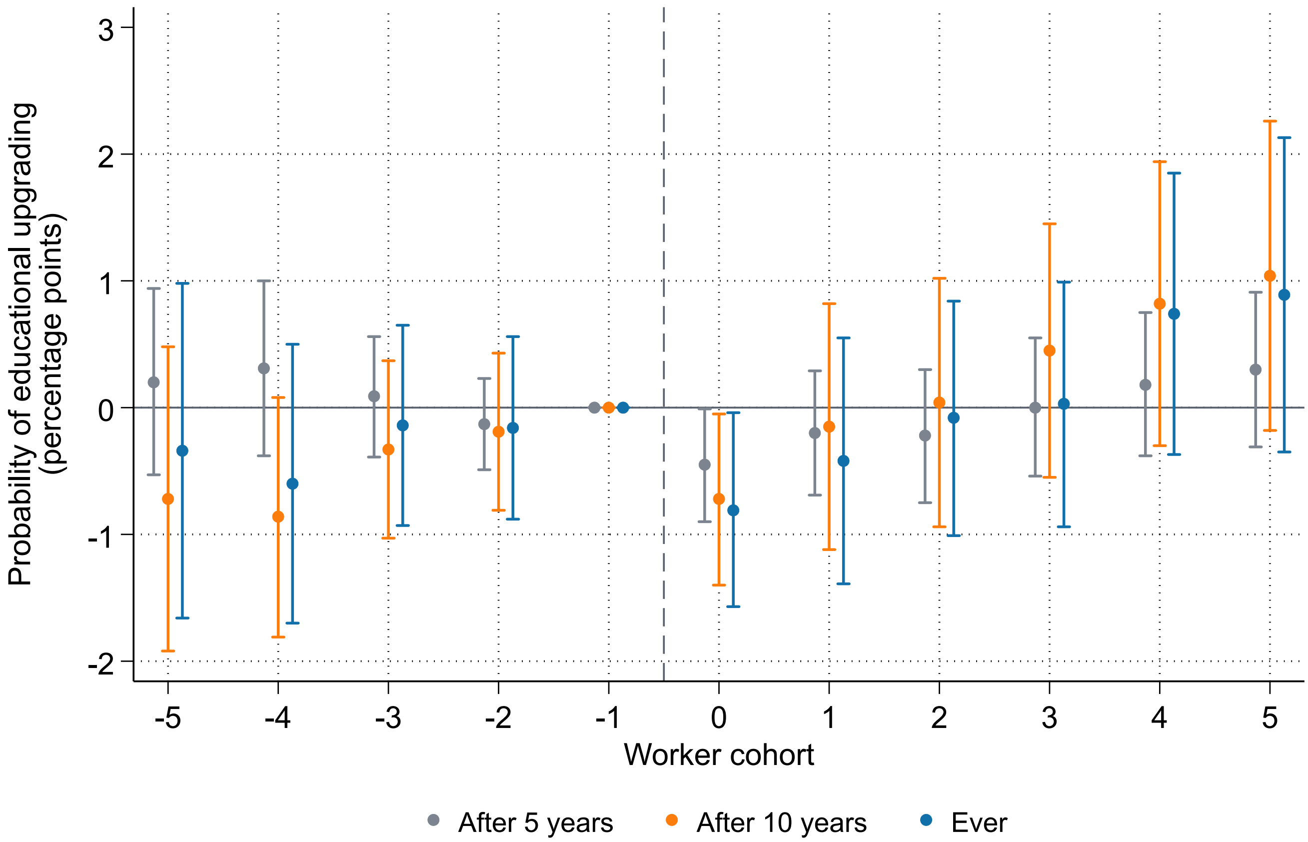
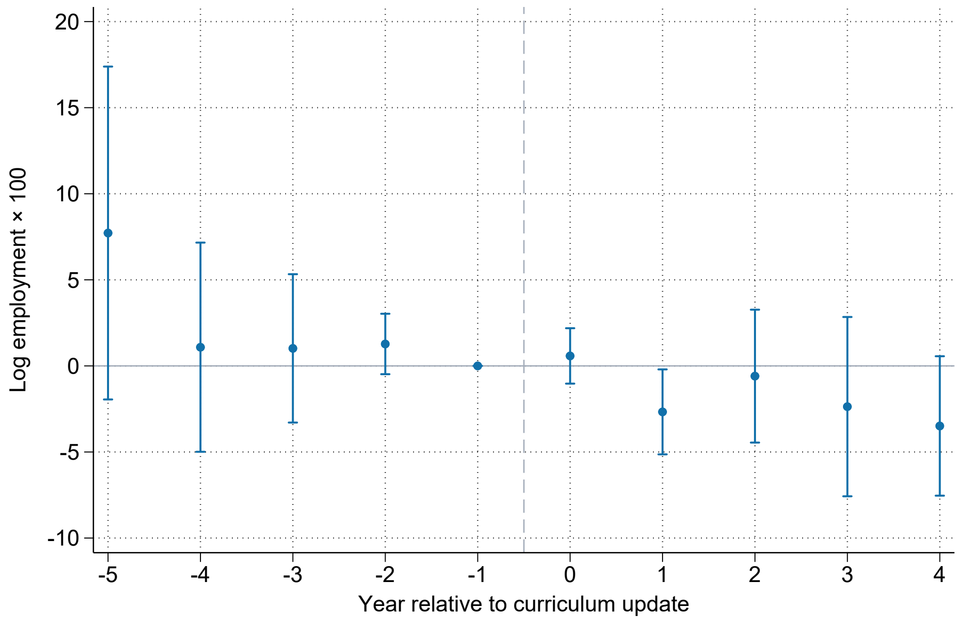


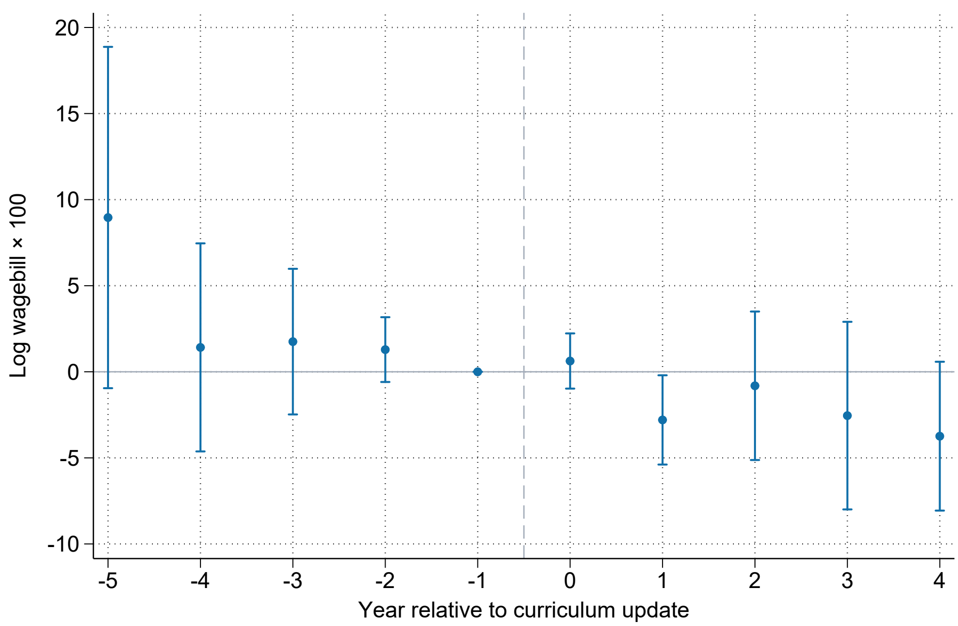
Figure reports stacked difference-in-differences estimates of equation (5), and 95% confidence intervals; estimated separately by year post training. Cohort 0 is the first cohort with the new curriculum; cohort -1 is the reference category. Standard errors clustered at the level of training occupation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

Figure A15: 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 updating events. 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.

A.4 Firm investments

Figure A16: Investment Impacts of Curriculum Updates, Extensive Margin Only

A. Overall

B. By technology exposure

Stacked difference-in-differences estimates of equation (7) using a dummy for investing as the dependent variable, and 95% confidence intervals. Based on 210 curriculum update events.

B Appendix tables

B.1 Data and measurement

Table B1: 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	3.85	2.58	4.09	2.61	3.85	2.61	4.18	2.70
Digital Tech Exposure – Exam	4.10	2.58	3.82	2.88	3.80	2.63	3.71	2.77
Overall Tech Exposure – Full Text	5.52	2.25	5.49	2.30	5.35	2.45	5.44	2.51

SD - Standard deviation.

Table B4: Most and Least Technology–Exposed Training Occupations

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

Ranked by number of linked digital patents.

B.2 Curriculum change

Table B5: Descriptive Statistics of Curriculum Keywords

	Total		Low tech		High tech	
	Mean	SD	Mean	SD	Mean	SD
Digital Keywords						
Occurrence of digital keywords (0/1)	0.32	0.47	0.18	0.38	0.46	0.50
Share of digital keywords (*1000)	0.07	0.20	0.03	0.08	0.11	0.26
Number of digital keywords	2.42	10.46	0.48	1.33	4.33	14.41
Team Keywords						
Occurrence of team keywords (0/1)	0.33	0.47	0.29	0.45	0.38	0.49
Share of team keywords*1000	0.61	1.25	0.61	1.35	0.62	1.14
Number of team keywords	1.79	5.32	1.12	2.43	2.44	7.02

Table B6: Curriculum Updates and Digital Technology Exposure — Exam Section Only

	A. Unweighted			
	(1)	(2)	(3)	(4)
Digital Tech Exposure	0.17*	0.19*	0.21*	0.20*
	(0.08)	(0.09)	(0.09)	(0.09)
N	10,433	10,433	10,433	10,433
	B. Weighted by initial employment share			
	(5)	(6)	(7)	(8)
Digital Tech Exposure	0.36	0.19	0.12	0.13
	(0.20)	(0.24)	(0.23)	(0.23)
N	10,433	10,433	10,433	10,433
Initial Curriculum Year FE	X	X	X	X
Year FE	X	X	X	X
Broad Occ FE		X	X	X
Broad Occ FE × Year FE			X	X
Initial Empl. Share				X

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

Table B7: Years Until Curriculum Update and Digital Technology Exposure — Exam Section Only

	A. Unweighted		
	(1)	(2)	(3)
Digital Tech Exposure	-0.37^{*}	-0.41^{*}	-0.41^{*}
	(0.16)	(0.17)	(0.17)
N	354	354	354
	B. Weighted by initial employment		
	(4)	(5)	(6)
Digital Tech Exposure	-0.35	-0.53^{*}	-0.46^{*}
	(0.24)	(0.24)	(0.23)
N	354	354	354
Initial Curriculum Year FE	X	X	X
Broad Occ FE		X	X
Initial Empl. Share			X

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

Table B8: Curriculum Updates and Overall Technology Exposure

	A. Unweighted			
	(1)	(2)	(3)	(4)
Overall Tech Exposure	0.21*	0.27*	0.36**	0.33**
	(0.10)	(0.11)	(0.12)	(0.12)
N	11,099	11,099	11,099	11,099
	B. Weighted by initial employment share			
	(5)	(6)	(7)	(8)
Overall Tech Exposure	0.65**	0.48*	0.50*	0.51**
	(0.23)	(0.23)	(0.20)	(0.19)
N	11,099	11,099	11,099	11,099
Initial Curriculum Year FE	X	X	X	X
Year FE	X	X	X	X
Broad Occ FE		X	X	X
Broad Occ FE × Year FE			X	X
Initial Empl. Share				X

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

Table B9: Type of Curriculum Update and Digital Technology Exposure – Weighted

	A. Content update only				B. Content update + Renaming			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Digital Tech Exposure	0.37*	0.32*	0.47**	0.50**	0.49**	0.50**	0.36*	0.35*
	(0.16)	(0.15)	(0.16)	(0.16)	(0.16)	(0.19)	(0.16)	(0.17)
N	10,546	10,546	10,546	10,546	10,499	10,499	10,499	10,499
	C. Content update + Aggregation				D. Content update + Segregation			
	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)
Digital Tech Exposure	0.54***	0.56**	0.40**	0.36*	0.08	0.09	0.10	0.11
	(0.15)	(0.19)	(0.15)	(0.15)	(0.06)	(0.06)	(0.07)	(0.07)
N	10,449	10,449	10,449	10,449	10,368	10,368	10,368	10,368
Initial Curriculum Year FE	X	X	X	X	X	X	X	X
Year FE	X	X	X	X	X	X	X	X
Broad Occ FE		X	X	X		X	X	X
Broad Occ FE × Year FE			X	X			X	X
Initial Empl. Share				X				X

Dependent variable: Dummy for curriculum update type. Linear probability models, weighted by employment size, coefficients multiplied by 100. Initial Curriculum Year FE in five year bins. Standard errors clustered at the 5 digit occupation level. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. Based on the yearly panel. 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.

Table B10: 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 B11: Most and Least Routine-Intense Training Occupations

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

Table B12: Most and Least Routine-Intense Training Occupations

Most Routine-Intense Training Occupations	Least Routine-Intense Training Occupations
A. Business service	
Legal assistant	Market and social research specialist
Media designer image and sound	Marketing communication clerk
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	Railway and road traffic clerk
Interior decorator	Driving operations specialist
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

B.3 Labor market impacts

Table B13: Descriptives of Vocationally Trained Labor Market Entrants, Stacked Sample

	Treated			Control		
	Mean (1)	SD (2)	Median (3)	Mean (4)	SD (5)	Median (6)
Age	24.05	3.04	24.00	24.06	2.84	24.00
Year of birth	1978	9.46	1979	1980	8.99	1982
Female	0.51	0.50	1.00	0.29	0.45	0.00
Daily wage (euros)	70.85	30.80	71.33	75.68	31.63	76.88
Annual daily wage growth	0.31	2.33	0.06	0.42	11.56	0.05
Years of training	2.80	0.50	2.88	2.91	0.54	2.92
Typical years of training	2.98	0.31	3.00	3.09	0.43	3.00
Annual days employed	267.66	140.43	365.00	267.03	141.23	365.00
Annual labor earnings	19,237	14,152	20,035	20,632	15,017	21,836
Firm size	499.38	2,383.01	39.00	619.32	2,606.82	57.00
N unique workers		33,964			36,168	

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 B14: Log Daily Wage Effects of Curriculum Updates

Treated × Cohort	All (1)	Excl. year of labor market entry (2)
-5	-0.33	0.22
	(0.85)	(0.81)
-4	-0.18	0.03
	(0.64)	(0.65)
-3	0.44	0.39
	(0.70)	(0.73)
-2	-0.59	-0.56
	(0.58)	(0.61)
0	0.44	0.45
	(0.60)	(0.62)
1	0.06	-0.47
	(0.70)	(0.68)
2	1.72*	1.62*
	(0.73)	(0.76)
3	2.00**	1.90**
	(0.71)	(0.72)
4	2.19**	2.19**
	(0.75)	(0.76)
5	1.77*	1.91*
	(0.84)	(0.85)
N Workers × Years	3,112,550	2,446,856
N Workers × Events	855,397	806,147
N Unique Workers	463,030	435,893
N Events	379	379

Stacked difference-in-differences estimates from equation (5). Individuals are included up to five years after graduation. The first cohort with the new curriculum is cohort 0. Coefficients and standard errors multiplied by 100. Standard errors clustered by occupation-times-event. $^{*}p < 0.05$, $^{**}p < 0.01$, $^{***}p < 0.001$.

Table B15: Descriptives of Occupational Incumbents

	Mean (1)	SD (2)	Median (3)	N (4)
Age	42.28	10.46	42.00	31,599,832
Year of birth	1961	11	1961	31,599,832
Female	0.36	0.48	0.00	31,599,832
Daily wage (euros)	89.55	42.22	90.31	25,145,852
Annual days employed	291.90	132.80	365.00	31,599,832
Annual labor earnings	27,205	20,563	28,286	31,599,832
Firm size	634	2,854	55	27,221,310
Job mobility (year-to-year):				
Occupation	0.10	0.30	0.00	31,599,832
Industry	0.10	0.30	0.00	31,599,832
Firm	0.67	0.47	1.00	31,599,832

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

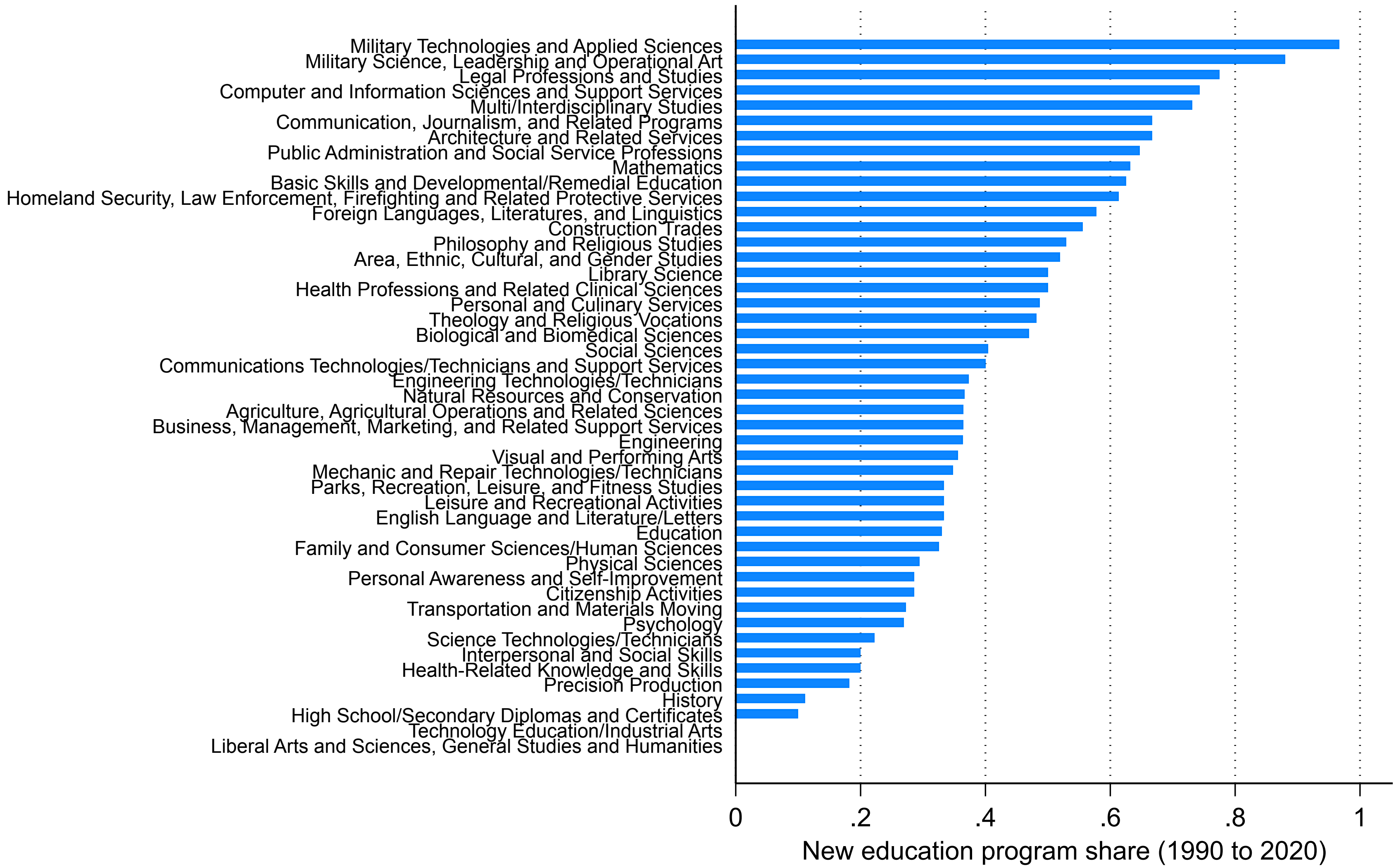


Figure plots the share of newly added degree programs by field based on CIP data.

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

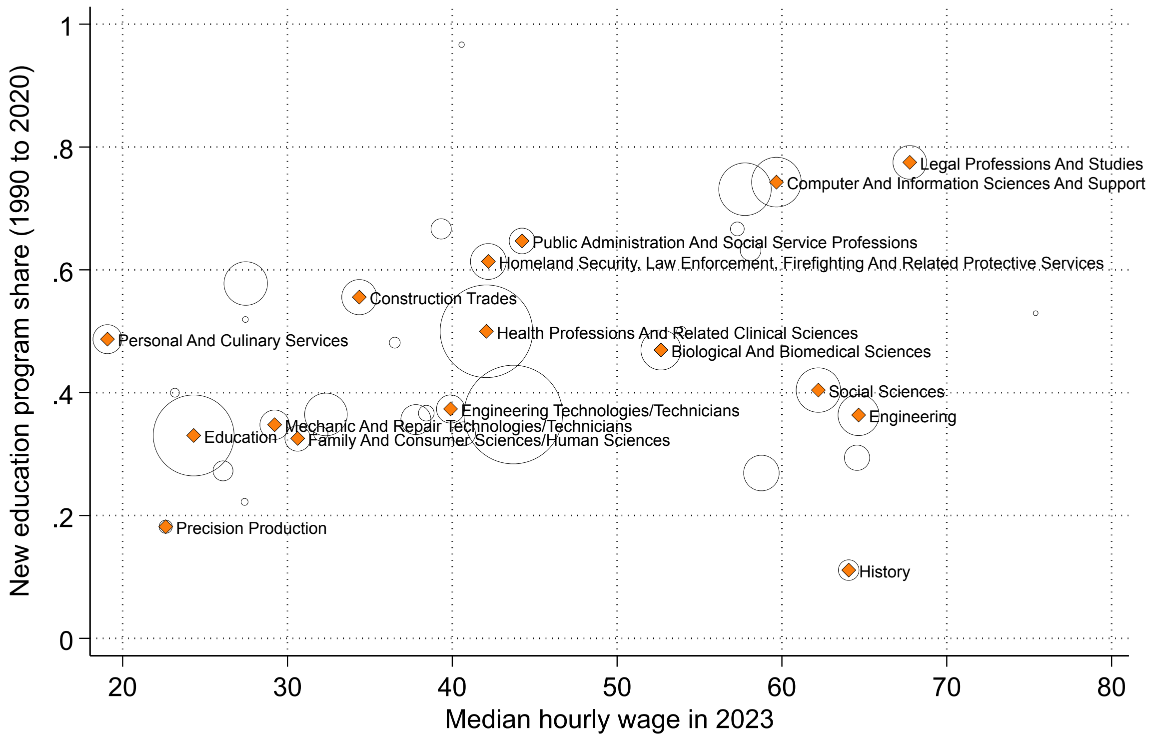


Figure plots the share of newly added degree programs by occupations ranked by median hourly wages, based on CIP data crosswalked to BLS data. The size of the circles reflects 2023 occupational employment shares.

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.[40] 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[41], 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, but this increase predates the update itself. We do note a dip in enrollment the year before the curriculum update, but this is transitory and does not reflect a longer pretrend nor persists after the 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

[40] 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.

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

never statistically significant. Further, there is a very small increase in the pass rate for students enrolling in updated training 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[42]: 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.[43]

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

[43] 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 A15, 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.

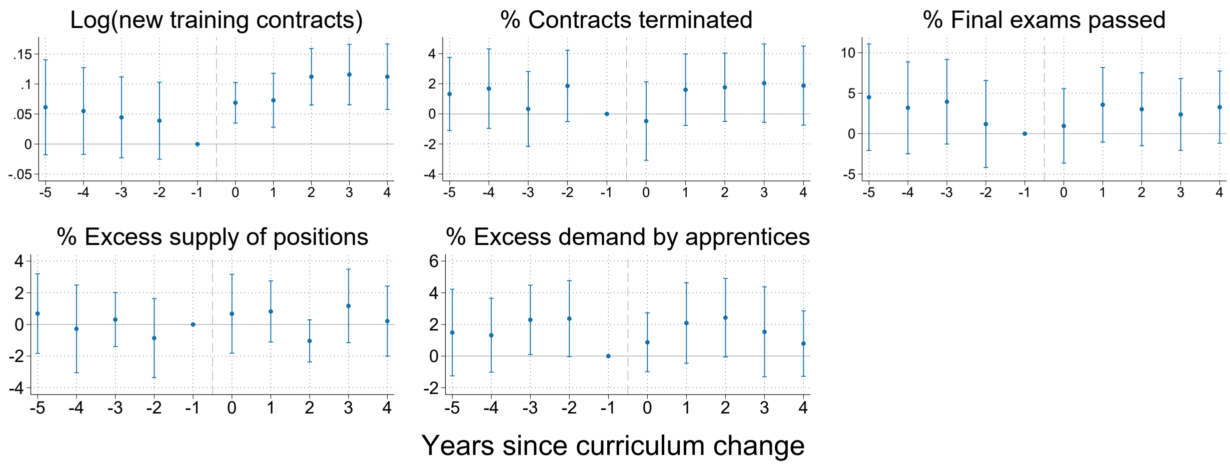
Table E1: Descriptives on Apprenticeship Positions and Trainee Composition

	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	7.90	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)	2.90	3.33	8,695

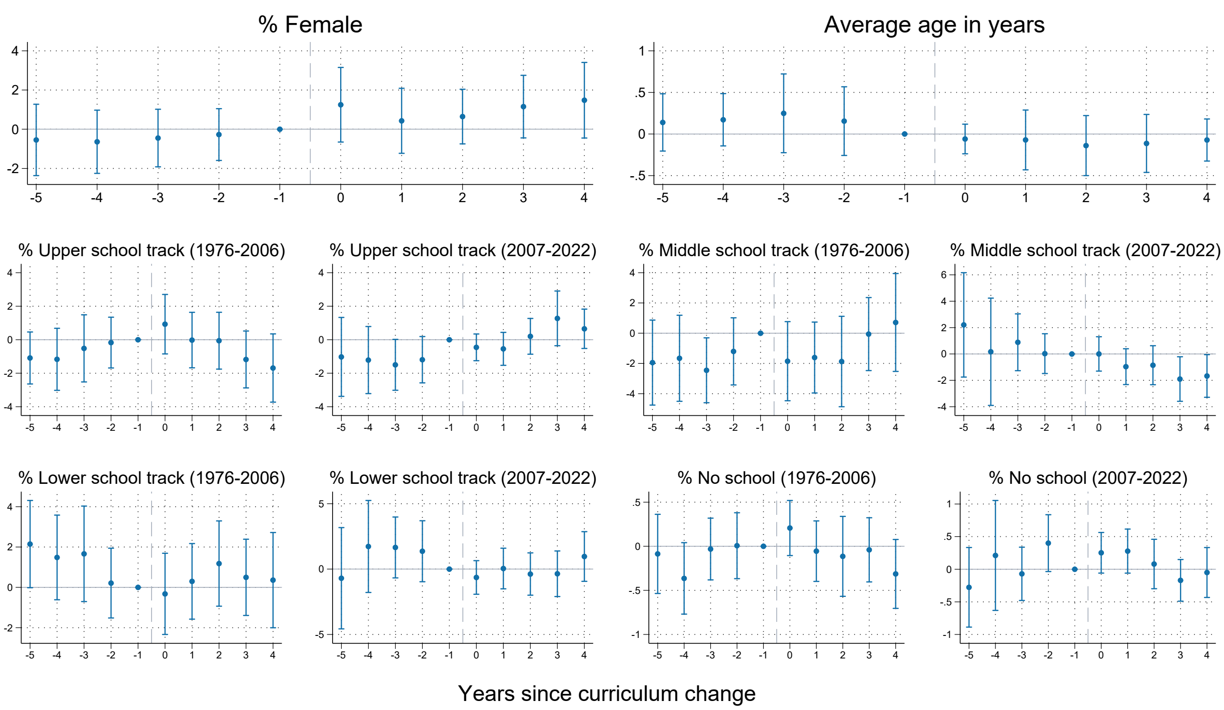
Mean and standard deviation in the initial year $\tau = -5$. N shows the number of observations included in the respective regressions: this varies across outcomes due to missing values.

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

A. Apprenticeship positions



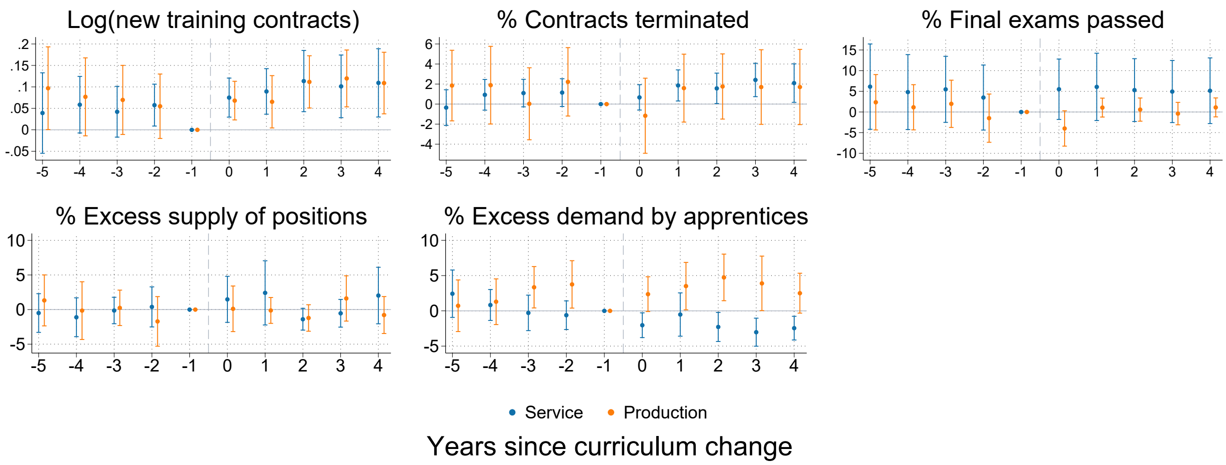
B. Trainee composition



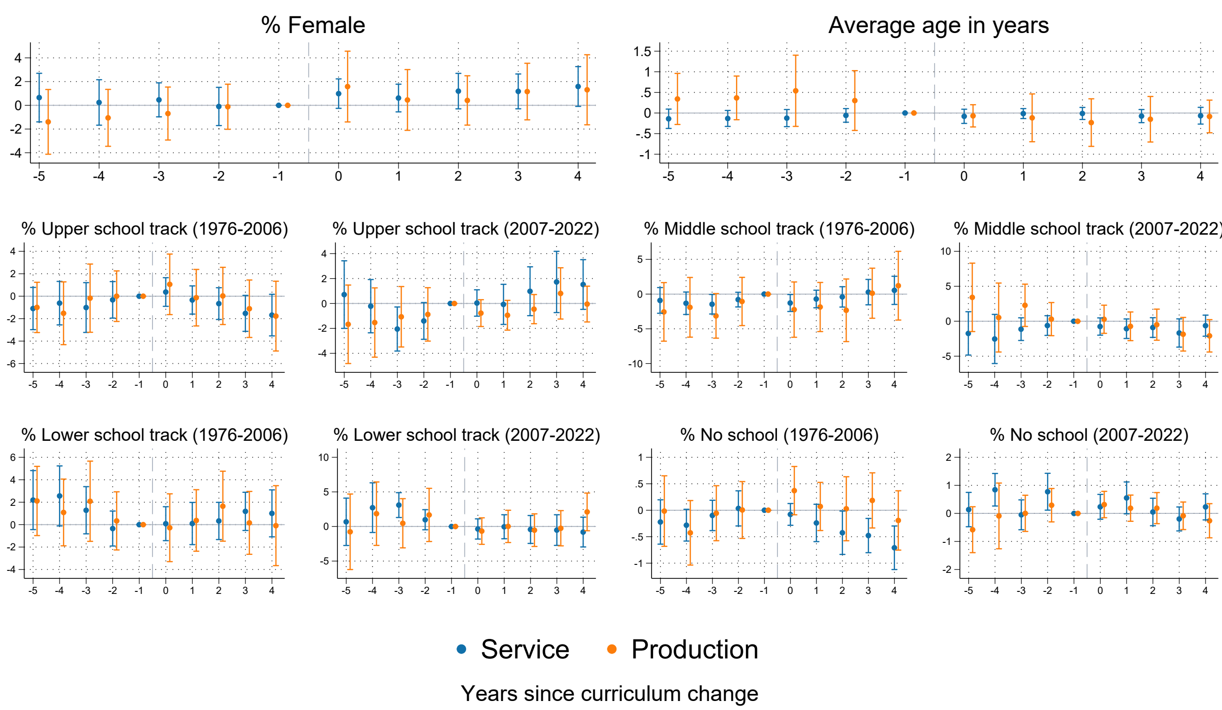
Stacked difference-in-differences estimates of curriculum updates on apprenticeship positions and trainee composition, comparing occupations with curriculum updates to occupations without updates. Based on 317 curriculum update events (pure content changes, aggregations without simultaneous segregations, 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.