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

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Abstract

We study how new digital technology reshapes vocational training and skill acquisition and its impact on workers' careers. We construct a novel database of legally binding training curricula and changes 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 technological advances drive training updates, with curriculum content evolving towards less routine intensive tasks, and greater use of digital and social skills. Using administrative employer-employee data, we show that educational updates help workers adapt to new demands for their expertise, and earn higher wages compared to workers with outdated skills. These findings highlight the role of changes in within-occupational skill supply in meeting evolving labor market demands for non-college educated workers.

Keywords: Technological Change, Vocational Training, Skill Updating
JEL: J23, J24, J31

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1 Introduction

Advancing technology transforms the labor market by altering skill demands, thereby changing the types of jobs that are available and the wages they pay. Both the automation of existing work and generation of new labor-using tasks require workers to adapt. An expansive literature on this 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 and which have been complemented by advancing technology, and on the labor demand impacts of specific technologies such as computers, robotics, or AI.[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 distinguishing workers by their years of schooling or (college) degree attainment (Deming, 2023). The evidence on the demand side highlights starkly changing demands for *specific* skills, including social skills and IT skills (Deming, 2017; Deming and Kahn, 2018), and transformed skill requirements *within* jobs (Spitz-Oener, 2006; Atalay et al., 2020). These changes in skill demand are quite distinct from increased educational requirements.

In this paper, we study a different way in which education races against technology, by documenting how occupation-specific skill supply adapts through changes in educational content. 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, highlighting a potentially important channel through which the labor market adjusts to changing skill demands. These adjustments indicate that advancing technology need not only lead to worker skill obsolescence but may also generate new demands for worker expertise.

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

[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).

improve labor market outcomes for affected workers, reflecting augmented expertise?

Vocational training in Germany is a full-time educational program following high-school, and is particularly relevant to study in the context of 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 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 empirical strategies to answer our research questions. First, to identify the effect of technological change on educational updates and content, we link vocational 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 model leveraging curriculum update events. This approach compares old- and new-skilled cohorts in an occupation that witnessed curriculum change to corresponding cohorts in occupations that did not witness curriculum

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

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 arguably evolve more smoothly over time.

We find that technological advances spur updates in vocational training: technology-exposed occupations are substantially more likely to receive curriculum updates, and these updates also arrive more rapidly. In particular, a standard deviation increase in technology exposure raises the annual probability of curriculum updates by 1.3 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. Using administrative employer-employee data, we show that this educational updating helps workers adjust to changing skill demands, leading to higher daily wages and annual 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 workers trained for the same occupation but with an updated curriculum. Wage returns to curriculum updates are more pronounced for workers trained in technology-exposed occupations, suggesting that revised training content helps workers in keeping pace with technological change. These wage returns from curriculum updates are not driven by changes in worker selection into updated training programs.

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.

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.

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 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.

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. 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; Schultheiss and Backes-Gellner, 2020; Kiener et al., 2023; Langer and Wiederhold, 2023; Cnossen et al., 2023; Buehler et al., 2023). 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. Section 5 concludes.

2 Data and measurement

We rely on three main data sources. The first two are training curricula and patent texts, which we link using Natural Language Processing (NLP) techniques. We describe these data sources below. The third 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. 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*,

[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).

BIBB).[4] Typically, it takes around one year after an update has been suggested by one of these partners to be agreed upon (Lorig et al., 2017), 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.

Our analysis focuses on occupations where a vocational training curriculum is observed ('training occupations').[5] 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.[6] 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.[7]

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.[8]

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

[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]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).

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

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

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

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.

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).[9] The 492 training occupations can be linked to 237 distinct KldB occupations (henceforth: occupations).[10]

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).[11] 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

[9] 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.

[10] 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.

[11] 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.

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-paid jobs compared to other occupations in the German economy.

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 Woodcarvers, Gilders, Glass blowers, Brass instrument makers, 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.[12] 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

[12] 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.

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. 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.[13] 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 A4 shows the most similar digital breakthrough patent for several example curricula, revealing sensible linkages. For example, "Self-gauging sensor assembly" (a sensor assembly for generating signals in response to the rotation of a body) is the most similar patent for the curriculum of Body and vehicle builders; "Process for making a prosthetic implant" is the most similar patent for the curriculum of Dental technicians; and "Computer travel planning system" is the most similar patent for the curriculum of Travel agents. Finally, we retain the 15% most similar patent-curriculum pairs, and sum them for each curriculum: the resulting occupational patent count is our measure of technology exposure. We perform this procedure separately for all patents and

[13] Patent texts are obtained from Autor et al. (2024). Appendix Table A1 shows the number of tokens contained in curriculum texts used for matching to patent texts—the average curriculum has 34,374 tokens.

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.

Figure 12 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 A5 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:

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

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 ($\frac{E_{jt_0}}{E_{t0}}$) to control for the possibility that larger occupations are more likely to receive curriculum updates.[14] 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.

[14] These occupations are not exactly one-to-one with training occupations as outlined in footnote 9.

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 predicts 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.

As reported in Appendix Table A2, 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%.[15]

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.[16] 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 depend on technology exposure? Here, we expect $\beta < 0$, reflecting that technology-exposed

[15] 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.

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

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 A2), 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 A6 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 A1), 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 A7 highlights that updates also arrive more rapidly. Appendix Table A8 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.[17] 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 A9 shows similar results when weighting models by occupational employment shares.

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 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 13 plots these local projection estimates, showing that technology exposure does not have an immediate effect on curriculum updates: coefficients are very close to zero for the first 15 years following technology exposure. From then on, coefficients increase and

[17] 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.

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

The previous section considered the occurrence and speed of curriculum updates. We now study 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 learning fewer routine tasks, and are using more digital technologies and social skills in their vocational training.

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.[18] 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

[18]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 A10 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 $i \in \{\text{RM, RC, NRA, NRM, NRI}\}$. 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.

Table 8 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.[19]

We document how the routine task intensity of curricula evolves over time by estimating

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

in the yearly panel where RTI_{kjt} is the routine intensity of curriculum k for training occupation j in year t (standardized to have a zero mean and unit standard deviation across curricula). β is the coefficient on a linear timetrend t, capturing the average annual change in routine task intensity 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.[20] 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 negative, and more so for occupations which are highly exposed to digital

[19] Appendix Table A11 shows the most and least routine intensive curricula separately for each of the five broad occupation groups. Appendix Figure A1 shows that routine task intensity is negatively correlated with occupational employment growth, as expected.

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

technology.

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 service occupations has a larger confidence interval).[21,22]

Digital technology use and social skills

We next 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

[21] Appendix Figure A2 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.

[22] 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.

"team". Descriptives are reported in Appendix Table A3. We again estimate equation (4), but replace the dependent variable by measures of the occurrence of these digital or team keywords, among updated curricula.

The top panel of Figure 15 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 $\times$ 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 15 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.[23]

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

[23] Appendix Figure A3 shows qualitatively similar results when not conditioning on curriculum change.

skills that are more complementary to digital technology, including reductions in routine task intensity. But does having 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 explore those implications here.

4.1 Sample construction

We use SIEED data (Berge et al., 2020)[24] 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 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 B 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

[24]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.

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.[25]

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).[26] 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 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 'new-skilled' and 'old-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, which we define as vocationally trained workers in the first 5 years since the end of their training. We estimate

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

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

Update_j is a treatment dummy indicating whether occupation j has seen an update of its training curriculum at some point during our time window: for each separate training update, this separates our treatment group (workers in occupations with a curriculum change) from our control group (workers in occupations without curriculum change).[27] Specifically, control

[25] As a robustness check, we will consider training for a occupation as updated only if the curriculum for training occupation constitutes the largest share of apprentices is updated.

[26] 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.

[27] Note that treatment is defined by the occupational training workers have received, not the occupation of employment after finalizing training. Workers need not be (nor remain) employed in the occupation they received vocational training for: since such occupational choice is an outcome, we do not use it to define

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 $c = 0$ as the first cohort trained in the new curriculum: as such, all treated cohorts $c \geq 0$ have also been trained in the new curriculum, while treated cohorts $c < 0$ have been trained in the old curriculum. We focus on workers 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).[28] 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 year by event.

For each event, we draw all treated workers and an equally large random sample of control workers — with a minimum of 100 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 work with training spells. We drop events with fewer than 20 treated workers in our data: this leaves a total of 380 curriculum update events and 379,537 unique treated individuals. Our control group consists of 149,160 unique workers, who may appear in several events.

Note that this approach uses repeated cross-sections of worker cohorts rather than a worker panel, as pre-update outcomes are not observed within workers for labor market entrants. Hence, the first difference in our differences-in-differences 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.

treatment, but will study this as a potential margin of adjustment.

[28] 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).

The second difference is the difference in outcomes between treated workers who were trained in occupations that have seen an update (irrespective of whether the individual worker has received the old or new curriculum) 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 estimate the treatment effect relative to the pre-treatment cohort $c = -1$. We will consider a range of worker outcomes: log daily wages, log annual earnings, non-employment, job mobility (across occupations, industries, and firms), and later educational outcomes. For the case of log wages, for example, we expect positive post-treatment estimates ($\beta_{c\geq0} > 0$), reflecting that workers entering with updated skills in occupation j have higher wages over the first five years of their career than past entrants without updated skills, relative to matched 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})—potential work experience, 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 workers, and (iii) SUTVA. Below, we provide empirical support for these assumptions in several ways.

Table 9 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 29 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 (551 workers on average), although the median firm size is 38 workers. Appendix Table A12 shows corresponding descriptives for the stacked sample, separately for treated and control group workers.

4.3 Do curriculum updates improve labor market outcomes?

Figure 16 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 (potential) curriculum reform. We find significant positive wage effects to curriculum updates for workers on average over their first five years after graduation from vocational training. These effects are up to 3% higher daily wages for graduates of the new curriculum compared to graduates from the old curriculum— relative to a control group of graduates in occupations with no curriculum update. This is striking since we are comparing workers trained for the exact same occupation, but with an updated curriculum. This finding highlights that educational content is racing to keep up with changing skill demands, and graduates with updated skills earn a significant wage premium.

Wage premia are visible for cohorts two years after the curriculum update and onward, but not found for the first two cohorts trained in the new curriculum (the point estimates indicate an imprecisely estimated wage return of around 1%). One potential explanation for this pattern is that there is a compliance issue for the earliest cohorts, if curriculum updates are mandated too rapidly for the majority of training firms to implement them. As a result, most workers in the first cohorts could still be trained in the old skill set. Alternatively, the first cohorts of workers could be more likely to remain in the largest firms close to the technology frontier, where new skills are less scarce and therefore less economically valuable. The wage returns to new skills then emerge as subsequent new-skilled cohorts are absorbed by other firms. We will consider worker mobility patterns in the next version of this paper. Wage returns increase for subsequent cohorts, peaking for the cohort trained four years after the curriculum update and diminishing for the final cohort we consider. This is expected if new-skilled workers become less scarce as prior cohorts with updated skills have already entered the labor market.

Table 10 provides the corresponding estimates for our main specification in column 1, as well as two alternative specifications in subsequent columns. 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 column 3, we next restrict the sample to workers who complete their vocational training within the typical duration, removing those who graduate faster or more slowly. This has the benefit of making cohorts and years isomorphic, unlike in our baseline model where worker cohorts who started training in the same year enter the labor market at different points in time. We find our results are similar in this sample.

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 Figure 17, and also shown in Appendix Table 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 already emerge for starting wages, and continue accruing in the next three years of the career. An additional benefit of the estimates by potential experience is that our baseline specification potentially contains 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 17 are therefore better identified if there are spillover effects.

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 Figure 18 and Table 11. As for daily wages, we find significant annual income increases from training in updated curricula. Estimated effects are similar in magnitude to the daily wage impacts (up to 3% higher annual wages over the first five years post training), suggesting the main margin of adjustment is through wages earned rather than days worked as expected among this group of early career workers.[29] We find that these estimates increase somewhat in magnitude when excluding the first year of labor market entry (column 2 in Table 11) and are similar (though now less precisely estimated) when restricting the sample to students who complete their vocational training degrees in the amount of time that is typical for their training occupation (column 3 in Table 11).

We also 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 advancing technology partially substitutes for workers' skills and curriculum updates provide a skill set that is more complementary to these technologies (see Section 3.2), we would expect to see wage returns of curriculum updates for workers trained in technology-exposed jobs.

Figure 19 reports wage returns to curriculum updates separately by technology exposure,

[29] Models estimated for annual days in employment, shown in Appendix Figure A4, confirm no significant impacts on the employment margin.

defined as occupational exposure being above or at or below the median exposure, as before. We confirm that curriculum updates for technology-exposed occupations yield wage returns for new-skilled worker cohorts, and these wage premia are higher than for less technology-exposed occupations, especially for later cohorts. While no difference is visible for the first three 'new-skilled' cohorts, cohorts trained in the new curriculum three to five years after it was first updated earn 4.6% (cohort 3), 6.4% (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 2.2%, 1.6% and 0.9%, where the last two estimates are not statistically significant. This suggests skill updates spurred by advancing technology impart larger and longer-lasting labor market advantages.

4.4 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 a separate dataset (DAZUBI) 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 trainee observables before and after curriculum updates in training programs which were updated versus those that were not. The estimating equation is

$$Y_{jt} = \sum_{\tau} \beta_\tau \text{Update}_j \times I_\tau + \delta_j + \gamma_t + \varepsilon_{jt}, \tag{6}$$

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. Appendix Table A14 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 20 describes the apprenticeship positions: the number of training contracts, the share of these terminated before the end of training[30], and the pass rate among contracts surviving until the final exam. 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 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 Appendix Table A14).

Panel B of Figure 20 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[31]: 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, Appendix Figure A5 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.[32]

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

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

[32] Along with no changes in trainee composition, we also do not find any changes in *total* employment or

5 Conclusion and next steps

Do educational updates allow workers to better adjust to changing 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 middle- and low-paid jobs. 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 towards tasks that are more complementary to digital technology. Using administrative employer-employee data, we show that educational updates help workers adjust to changing skill demands, leading to improved wage outcomes compared to workers with outdated skills. In Germany, vocational curriculum updates are jointly decided by employer organizations, unions, and the Federal Institute for Vocational Education and Training: recent work suggests such collective decision-making may be important for ensuring worker skills remain relevant for the labor market (Katz et al., 2022; Kahn et al., 2023).

In a next version of this paper we will consider specific adjustment mechanisms underlying improved wage outcomes uncovered here, including mobility across occupations, industries, and firms; and further educational attainment. Moreover, we will consider longer-term outcomes for workers with updated skills. We will also identify the impacts of educational updates on occupational incumbents whose skills may depreciate, and consider whether there is evidence of incumbent retraining. Finally, our detailed curriculum text data allow us to further document educational content change by extracting newly added as well as obsolete skills, to distinguish between curricula where new skills have been added and those where the skill set has dwindled. This allows us to ask whether new additions to workers' skill set augment worker expertise and impart larger labor market advantages. These analyses further inform a nascent literature studying how occupational content evolves, and the roles played by task automation and new task emergence.

wagebills for training occupations around curriculum update events, using SIAB data. Estimates for these models are shown in Appendix Figure A6, 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.

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Figures

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

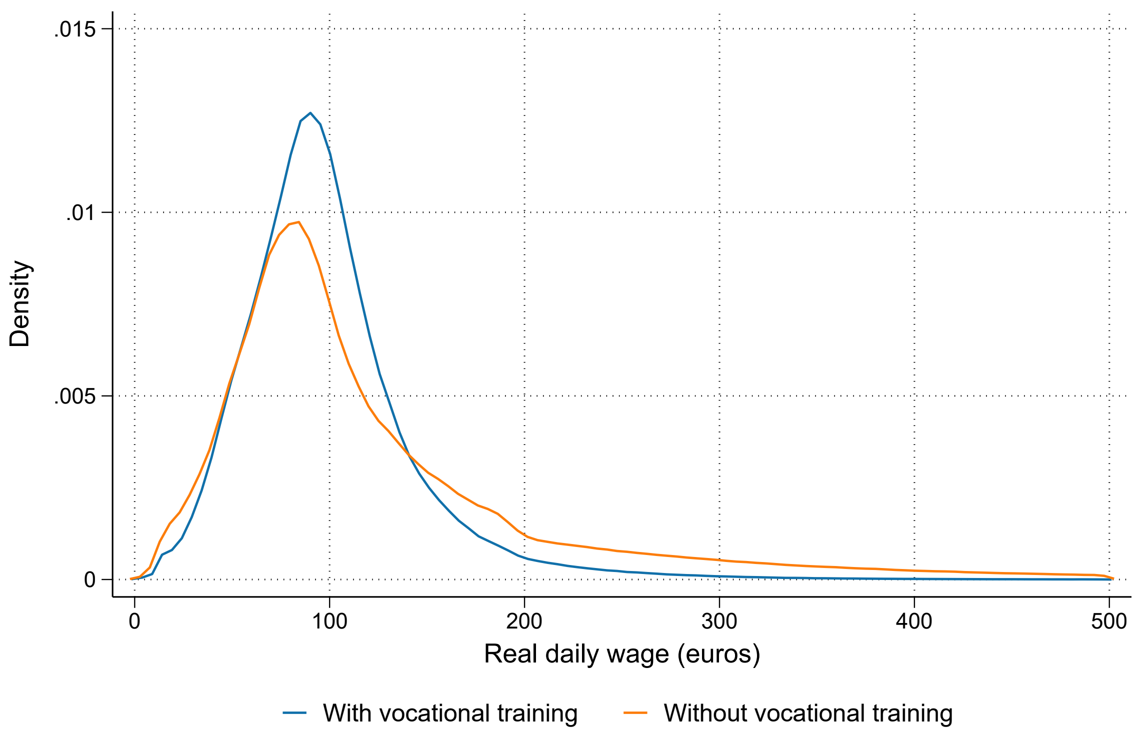


Figure plots the distribution of real daily wages (up to 500 euros) for vocationally trained workers versus all others based on SIAB data.

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

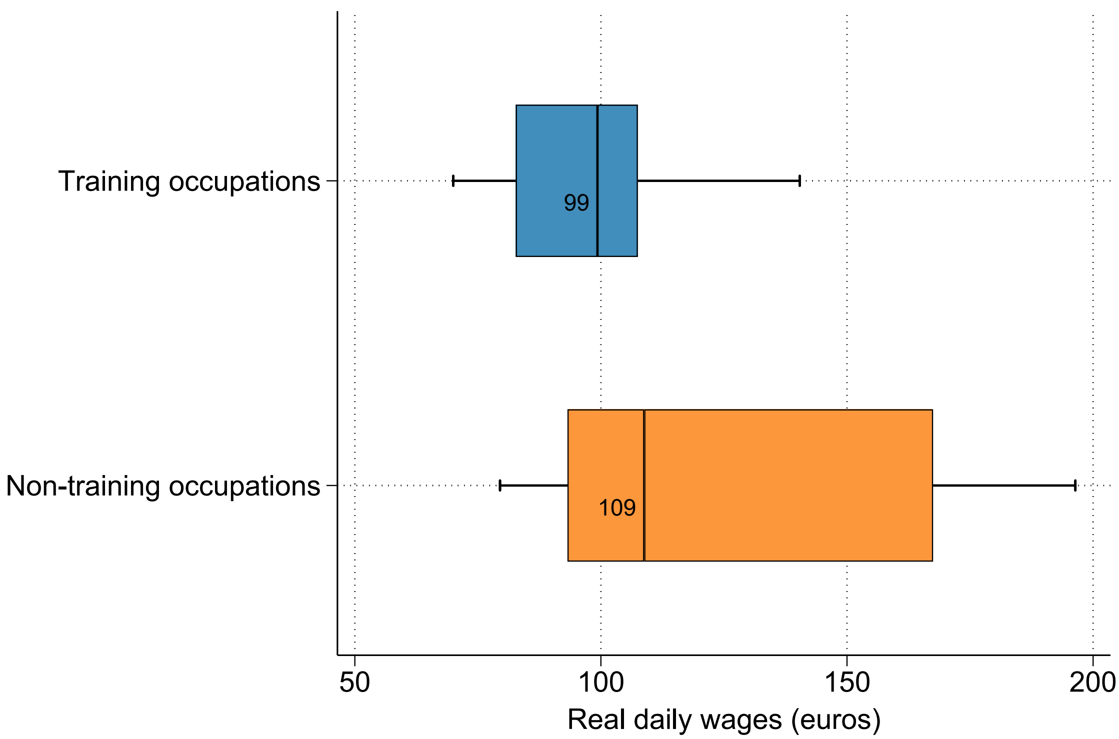


Figure shows a boxplot of real daily wages for occupations with and without a vocational training curriculum (base year for deflation: 2015) based on SIAB data. Vertical lines indicate the median; boxes reflect the interquartile range; and whiskers indicate the 10th and 90th percentiles. Occupations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

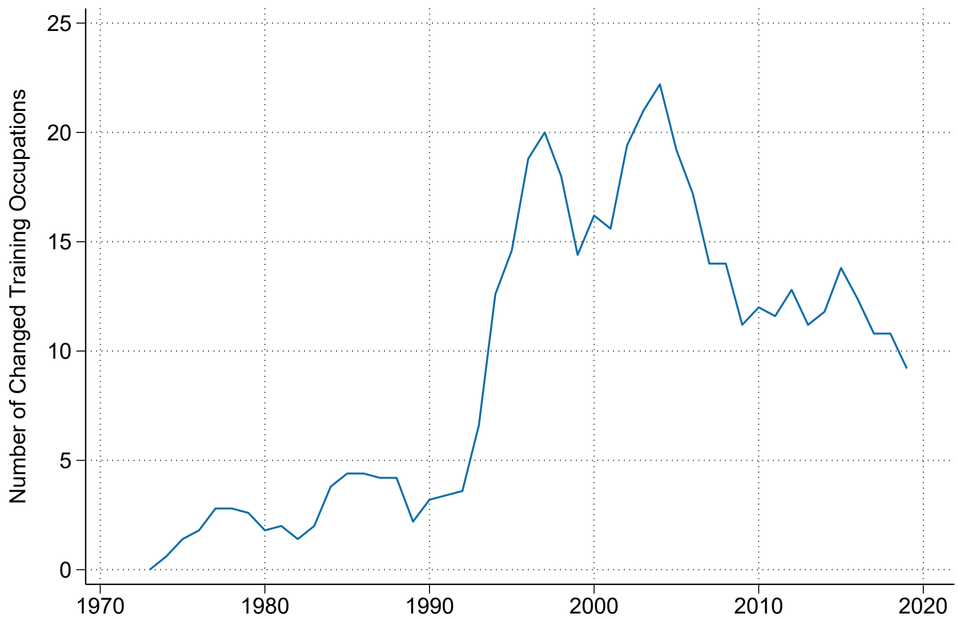


Figure shows the 5-year moving average of the number of curriculum changes by year.

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

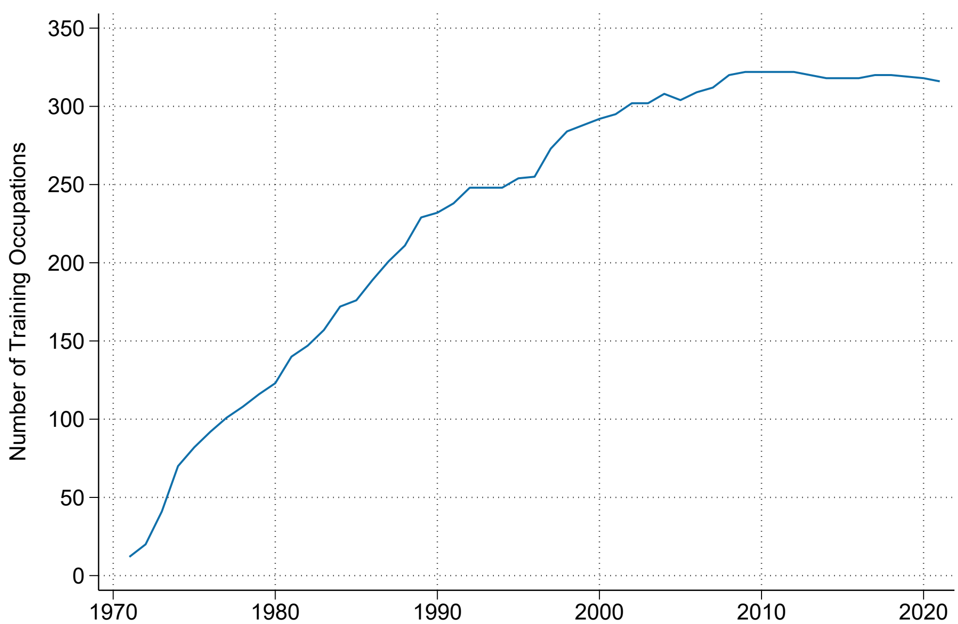
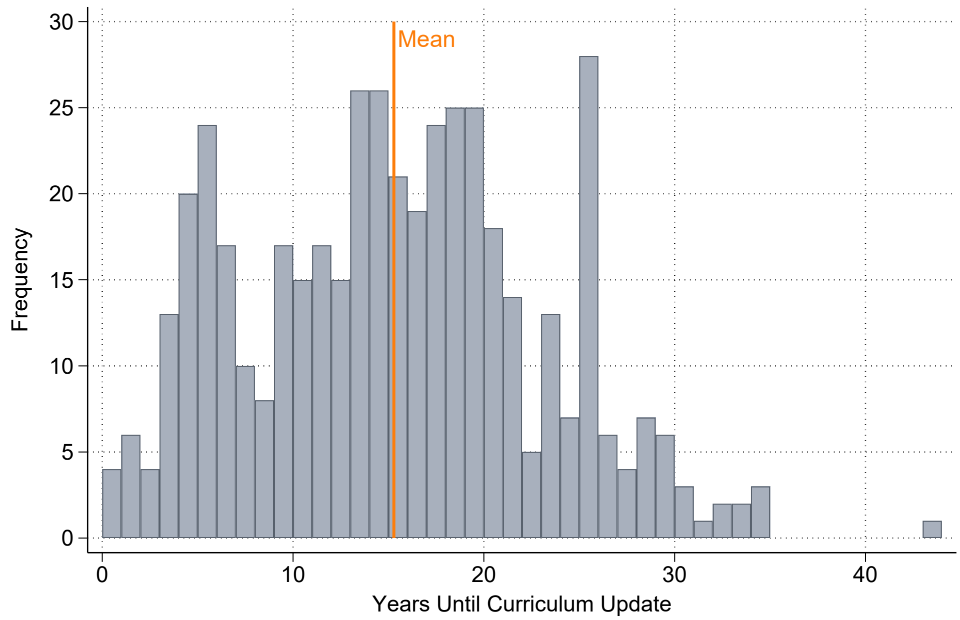


Figure shows the number of active training occupations in the national register after the introduction of the Vocational Training Act in 1969.

Figure 9: Years until Curriculum Update

A. Overall



B. By Broad Occupation Group

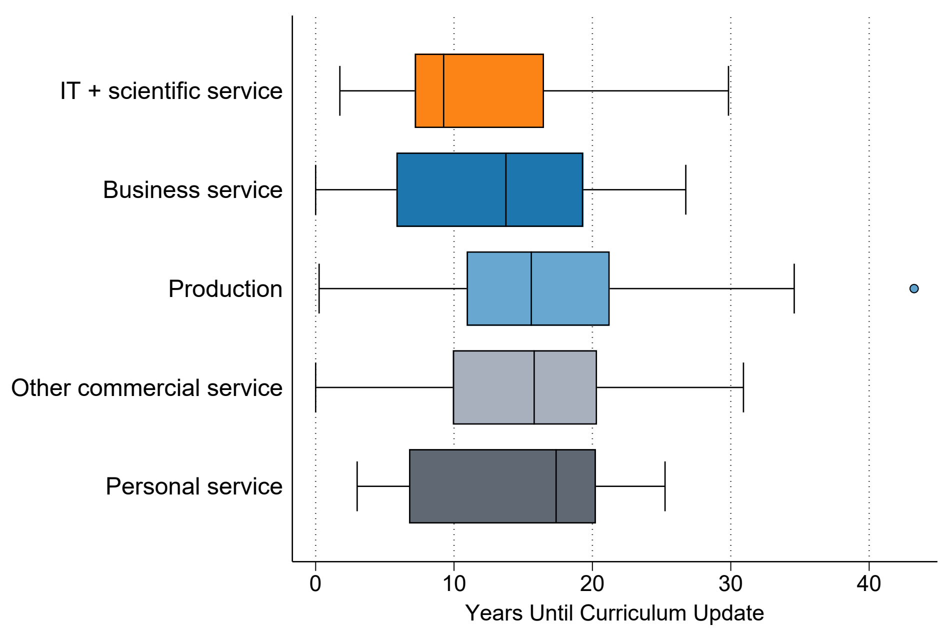


Figure shows the distribution of years until curriculum updates for initial training occupation observations ($N = 470$). Panel A shows the overall distribution across training occupations. Panel B shows a boxplot by broad occupation group. Vertical lines indicate the median; boxes reflect the interquartile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

Figure 10: Share of Breakthrough Patents by Technology Class

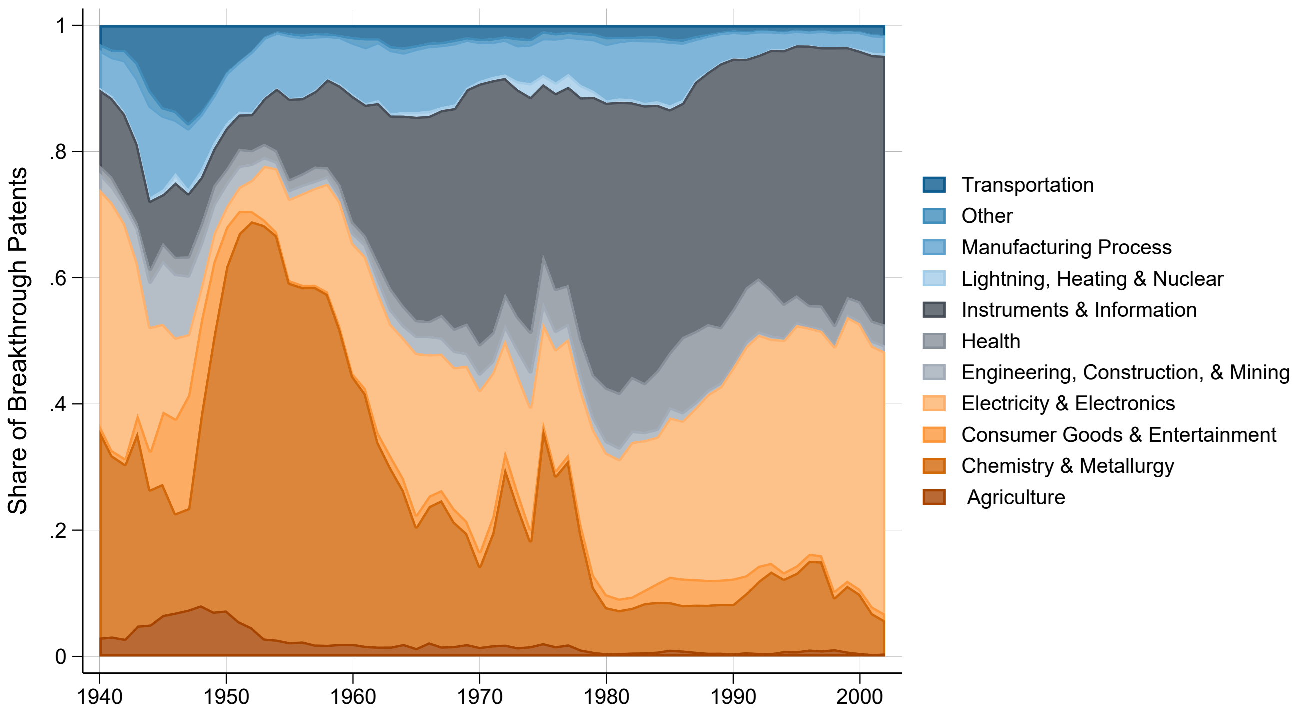
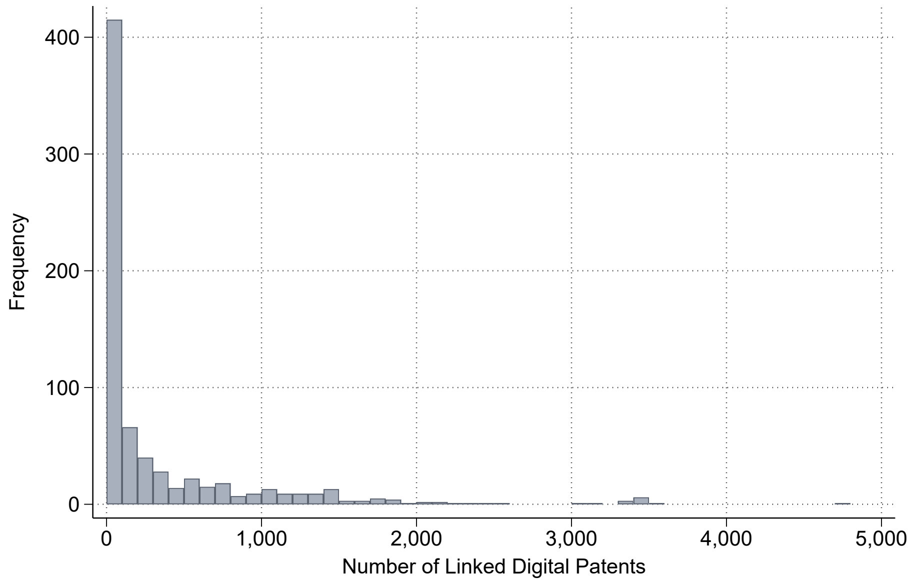


Figure shows the distribution of breakthrough patents across broad technology classes defined by Kelly et al. (2021). Over 1940–2002, we observe $N = 141,708$ breakthrough patents in Instruments & Information.

Figure 11: Digital Technology Exposure of Training Curricula

A. Overall



B. By broad occupation group

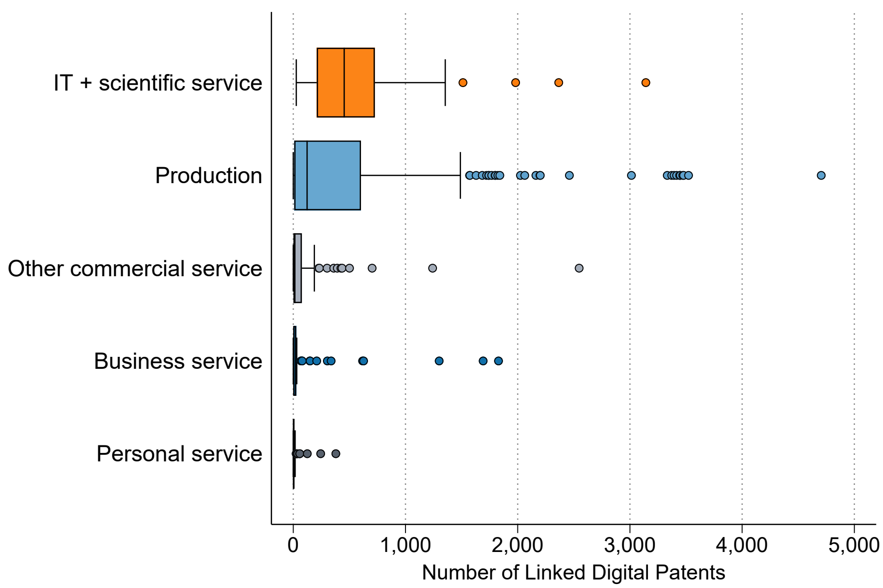


Figure shows the distribution of linked digital patent counts for initial training occupation observations ($N = 791$). Panel A shows the overall distribution across training occupations. Panel B shows a boxplot by broad occupation group. Vertical lines indicate the median; boxes reflect the interquartile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

Figure 12: 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 13: Impacts of Digital Technology Exposure on Curriculum Updates Using Local Projections

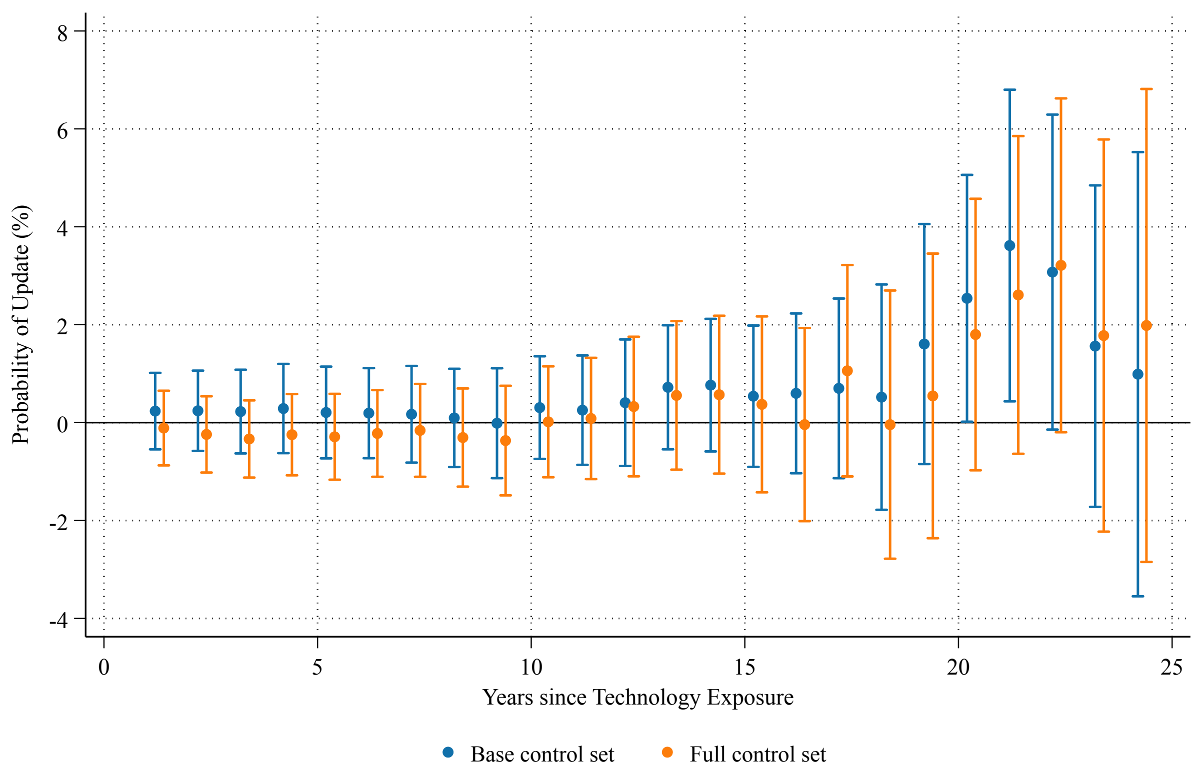


Figure presents estimates of equation (3). The dependent variable is a dummy for the curriculum being updated (conditional on not having being updated yet). Coefficients multiplied by 100. Standard errors clusted by occupation, whiskers represent 95% confidence intervals.

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

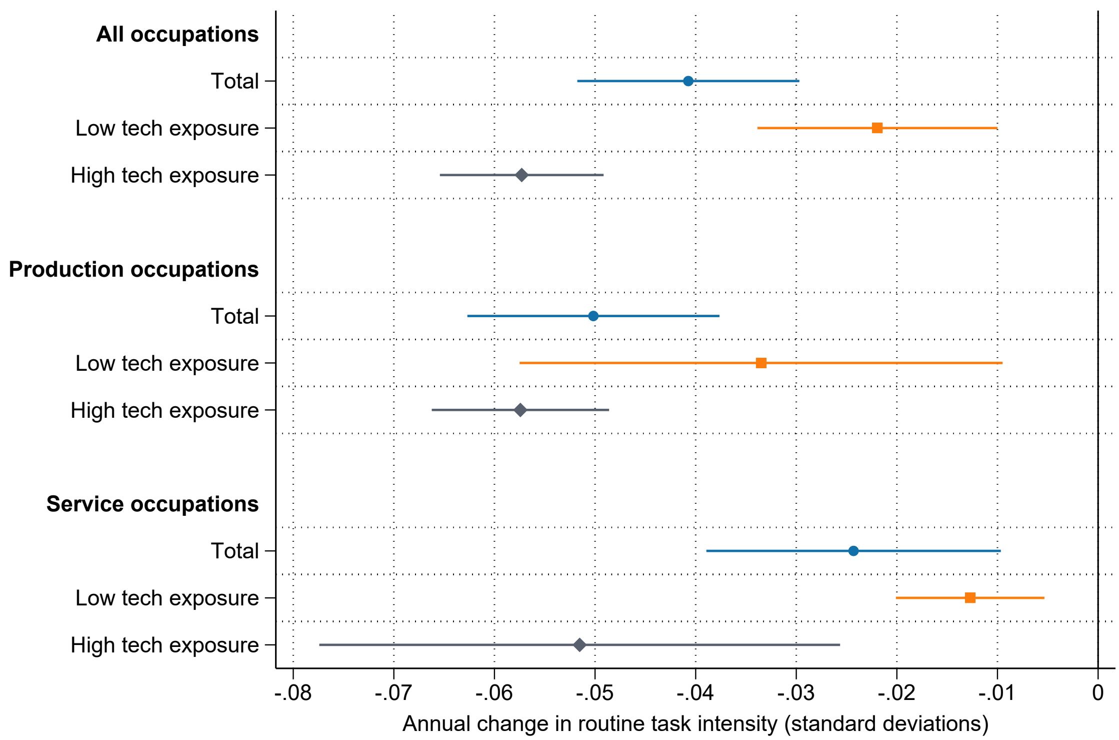


Figure reports coefficients on a linear timetrend, from a regression of routine task content in vocational training curricula (see equation (4)), for the subsample of curricula with updates over 1976–2021. Horizontal lines reflect 95% confidence intervals. High tech (low tech) defined as curricula with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

Figure 15: Changes in Digital Technology and Social Skill Use in Updated Curricula, 1976–2021

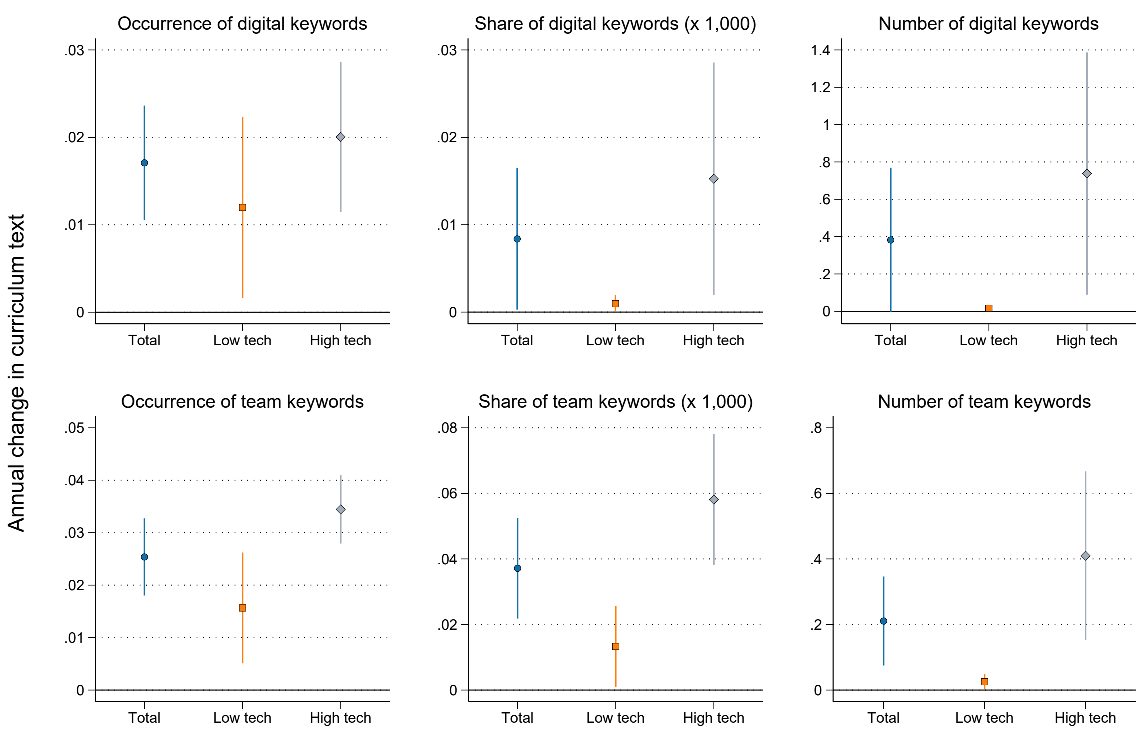


Figure reports coefficients on a linear timetrend, from a regression of keyword occurrence, keyword shares, or keyword counts in vocational training curricula (see equation (4)), for the subsample of curricula with updates over 1976–2021. High tech (low tech) defined as curricula with an initial digital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

Figure 16: Log Daily Wage Impacts of Curriculum Updates

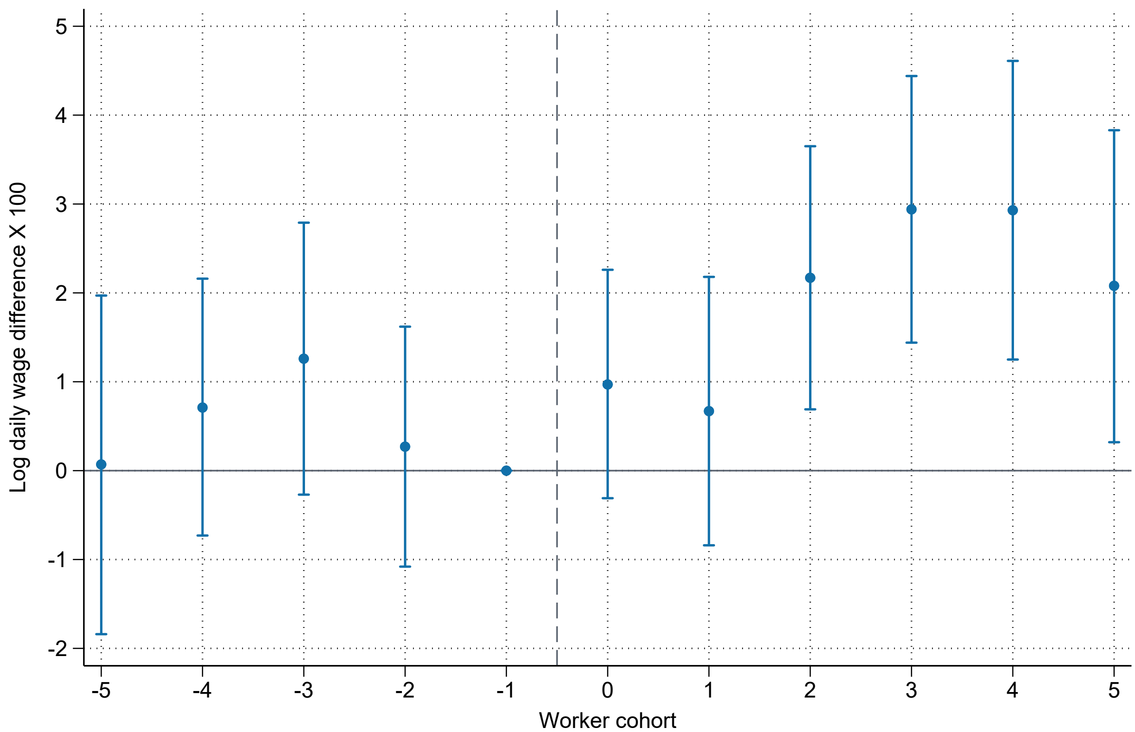


Figure reports stacked difference-in-differences estimates of equation (5), and 95% confidence intervals. Cohort 0 is the first cohort with the new curriculum; cohort -1 is the reference category. Individuals are included up to five years after graduation. Standard errors clustered at the level of training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

Figure 17: Log Daily Wage Impacts of Curriculum Updates By Experience

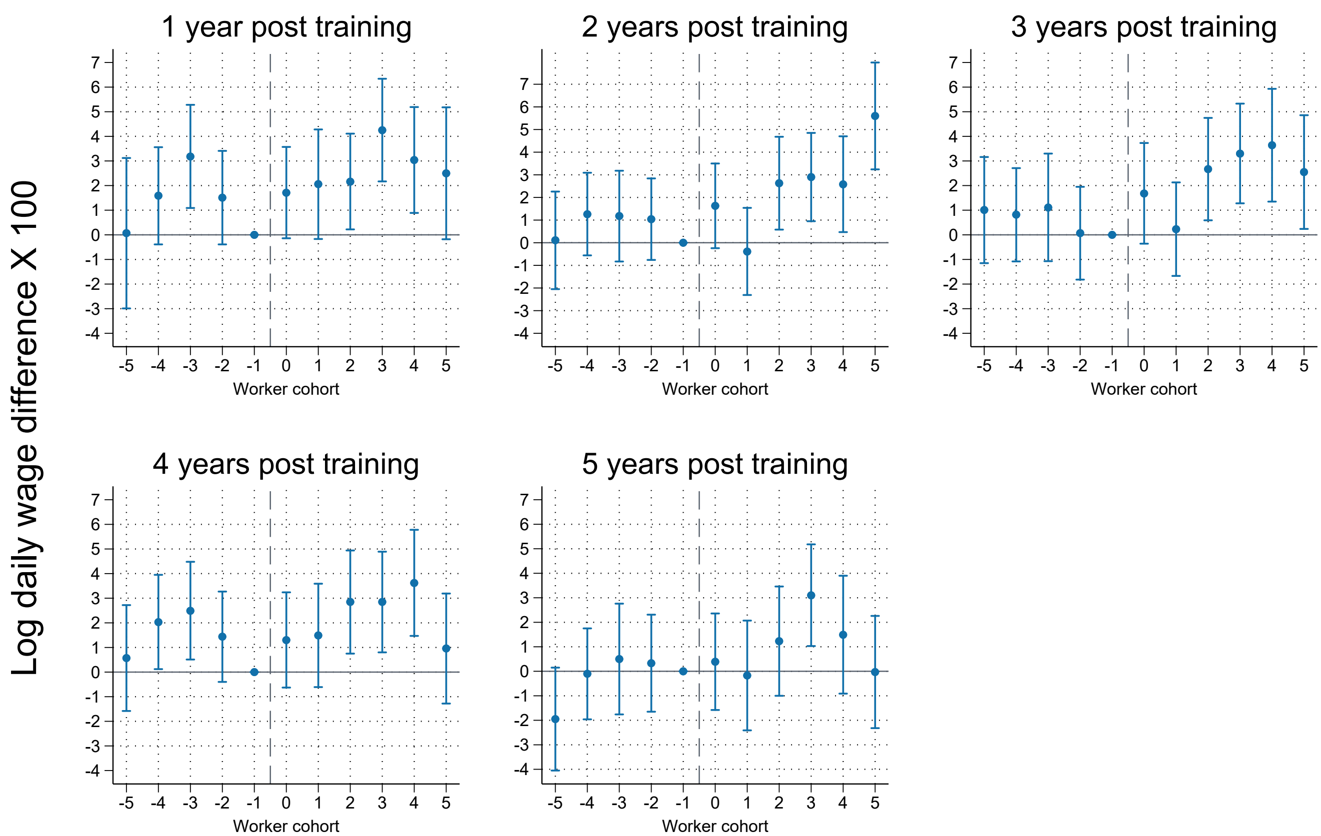


Figure reports stacked difference-in-differences estimates of equation (5), and 95% confidence intervals; estimated separately by year post training. Cohort 0 is the first cohort with the new curriculum; cohort -1 is the reference category. Standard errors clustered at the level of training occupation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

Figure 18: Log Annual Income Impacts of Curriculum Updates

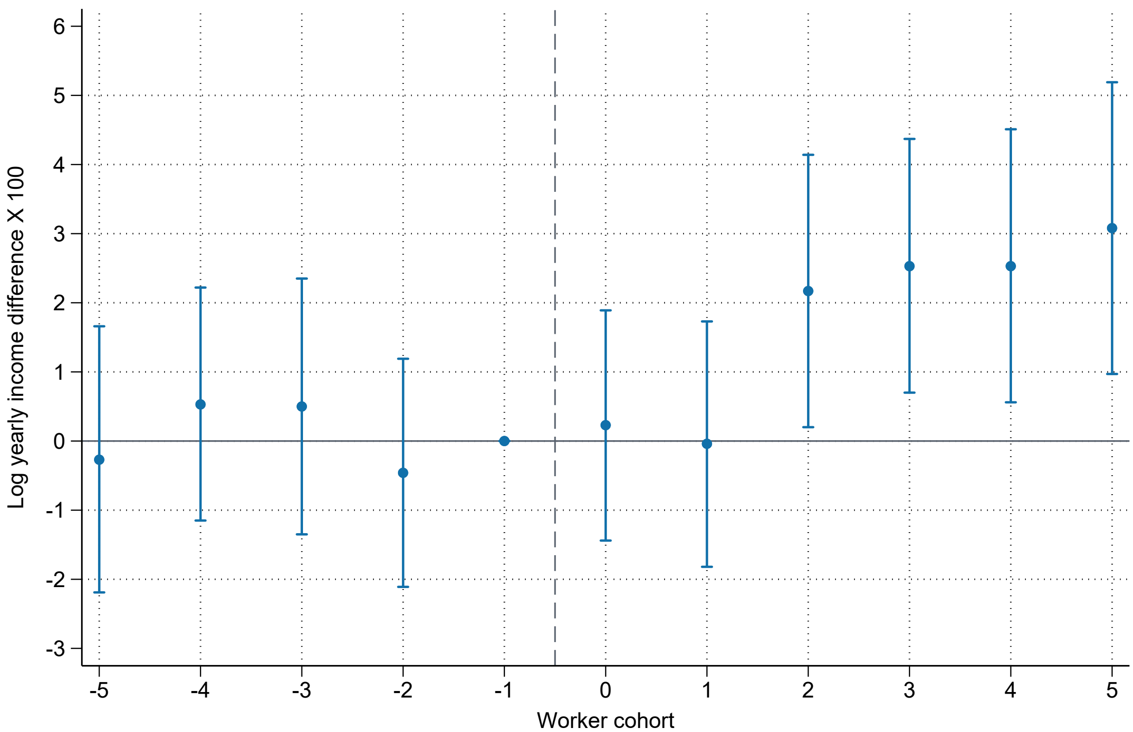
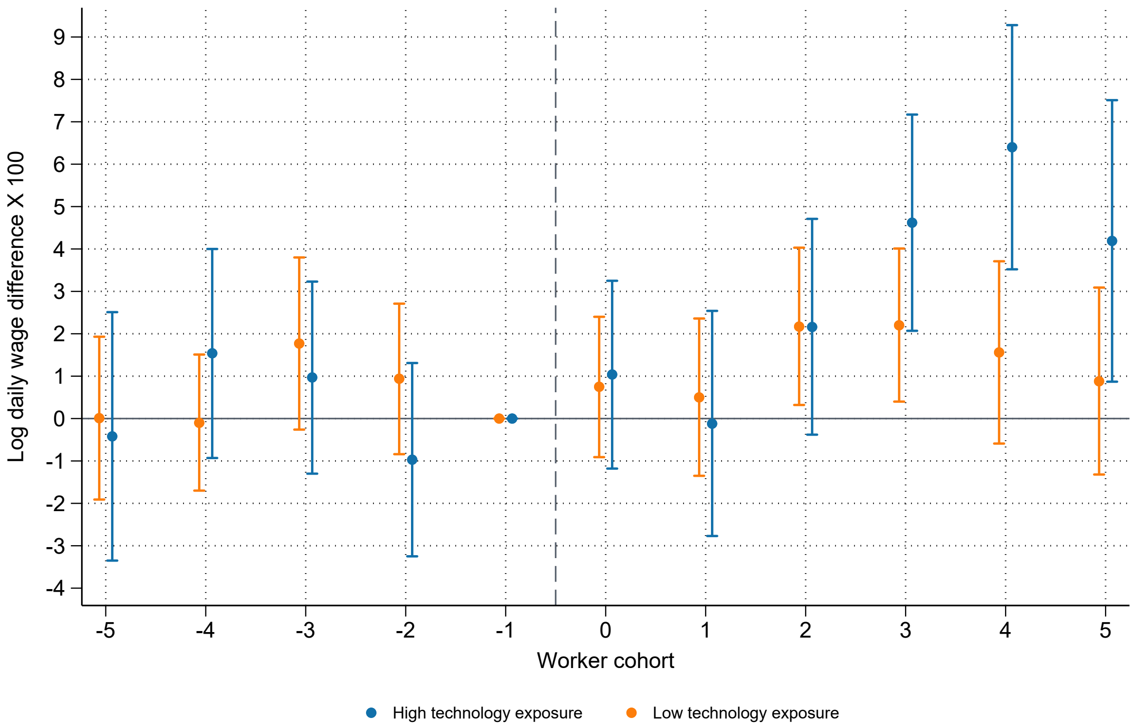


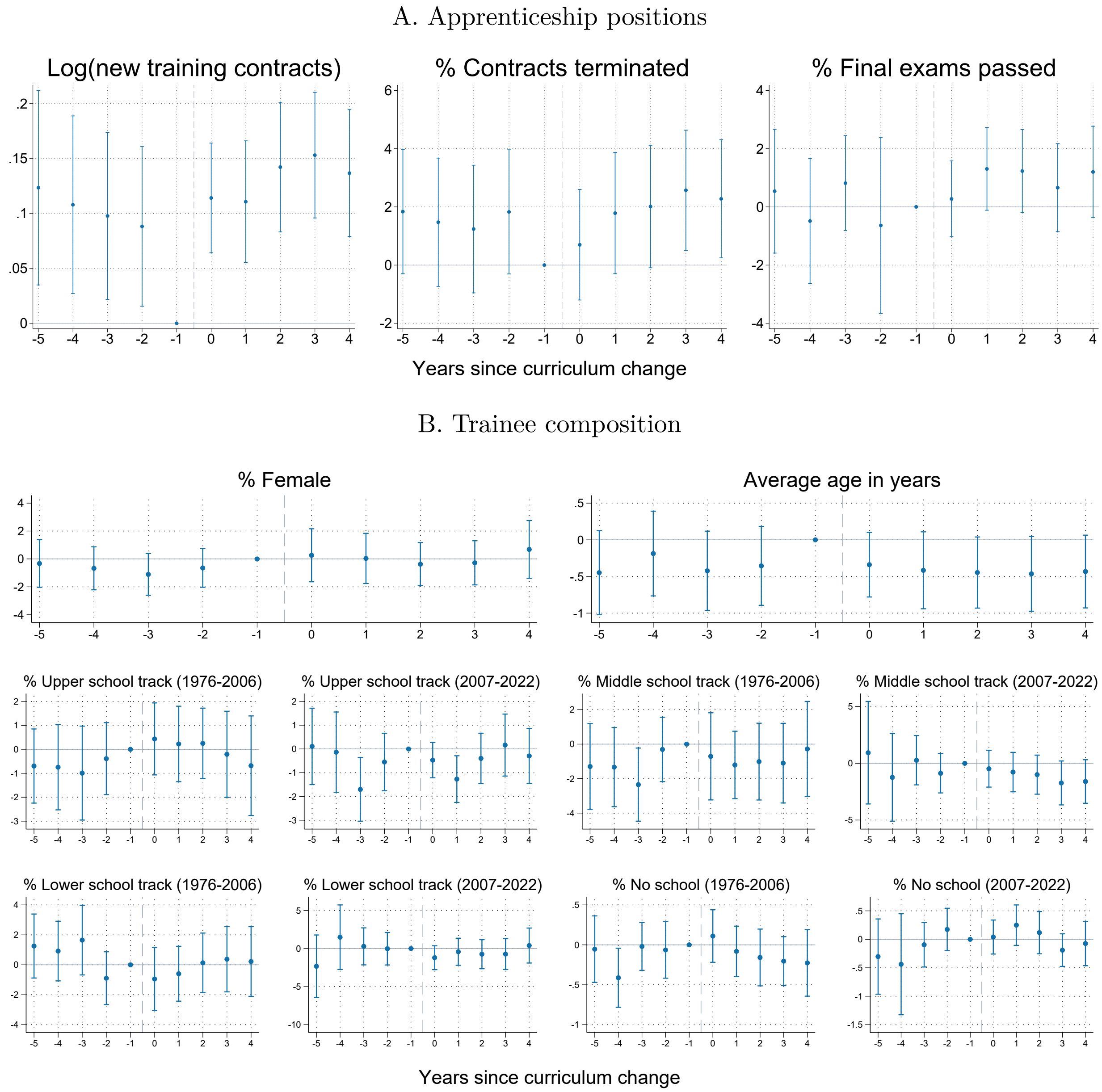
Figure reports stacked difference-in-differences estimates of equation (5), and 95% confidence intervals. Cohort 0 is the first cohort with the new curriculum; cohort -1 is the reference category. Individuals are included up to five years after graduation. Standard errors clustered at the level of training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

Figure 19: Log Daily 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 20: Apprenticeship Positions and Trainee Composition Before and After Curriculum Updates



Stacked difference-in-differences estimates of curriculum updates on apprenticeship positions and trainee composition, comparing occupations with curriculum updates to occupations without updates. Based on 317 curriculum update events 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. 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). % final exams passed available from 2010 onward; % female available from 1993 onward; average age in years available from 2007 onward.

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
Electrician	Production	0.09
Retail clerk	Business service	0.09
Automobile mechanic	Production	0.09
Electronics technician for aeronautical systems	Production	0.09
Decor template maker	Production	0.09
Chemical technician	IT + scientific service	0.08
Packaging technologist	Production	0.08
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
Toy manufacturer	Production	0.01
Wooden toy maker	Production	0.01
Industrial insulator	Production	0.01
Examples of Training Occupations Without Updates		
Reed instrument maker	Production	0.00
Brass instrument maker	Production	0.00
Glass blower	Production	0.00
Stage painter and sculptor	Personal service	0.00
Woodcarver	Production	0.00
Woodwind instrument maker	Production	0.00
Gilder	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: 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 9: Descriptives of Vocationally Trained Labor Market Entrants

	Mean (1)	SD (2)	Median (3)	N (4)
Age	23.28	3.02	23.00	592,555
Year of birth	1975	9.61	1975	592,555
Female	0.40	0.49	0.00	592,555
Daily wage (euros)	70.42	29.69	71.67	561,396
Annual daily wage growth	0.33	6.95	0.06	535,518
Years of training	2.82	0.53	2.88	592,555
Typical years of training	3.00	0.38	3.00	592,555
Annual days employed	268.44	138.27	365.00	592,555
Annual labor earnings	18,333	13,488	18,554	592,555
Firm size	551.63	2,740.79	38.00	592,555

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.

Table 10: Log Daily Wage Effects of Curriculum Updates

Treated $\times$ Cohort	All (1)	Excl. year of labor market entry (2)	Excl. atypical training duration (3)
-5	0.07	-0.02	-0.55
	(0.97)	(0.84)	(1.25)
-4	0.71	0.67	0.04
	(0.74)	(0.70)	(1.14)
-3	1.26	0.92	0.42
	(0.78)	(0.85)	(1.25)
-2	0.27	0.38	-0.82
	(0.69)	(0.74)	(0.96)
0	0.97	1.00	0.10
	(0.65)	(0.77)	(0.97)
1	0.67	-0.10	0.18
	(0.77)	(0.81)	(1.08)
2	2.17**	2.01*	2.86*
	(0.76)	(0.88)	(1.15)
3	2.94***	2.76***	2.39
	(0.76)	(0.82)	(1.34)
4	2.93***	2.68**	3.48*
	(0.86)	(0.93)	(1.37)
5	2.08*	2.01*	1.74
	(0.90)	(0.91)	(1.47)
N Workers $\times$ Years	3,006,461	1,936,755	1,566,212
N Workers $\times$ Events	710,262	636,312	365,076
N Unique Workers	456,214	406,796	230,645
N Events	380	380	380

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 11: Log Annual Income Effects of Curriculum Updates

Treated × Cohort	All (1)	Excl. year of labor market entry (2)	Excl. atypical training duration (3)
-5	-0.27	0.71	-1.14
	(0.98)	(1.02)	(1.57)
-4	0.53	1.51	0.46
	(0.86)	(0.98)	(1.50)
-3	0.50	1.02	-0.53
	(0.94)	(1.02)	(1.44)
-2	-0.46	-0.11	-1.65
	(0.84)	(0.95)	(1.20)
0	0.23	0.61	1.58
	(0.85)	(1.03)	(1.44)
1	-0.04	0.02	1.11
	(0.91)	(1.04)	(1.55)
2	2.17*	3.03*	4.10*
	(1.00)	(1.20)	(1.88)
3	2.53**	2.25*	3.38
	(0.94)	(1.11)	(2.09)
4	2.53*	2.70*	3.55
	(1.01)	(1.17)	(2.27)
5	3.08**	3.69**	3.59
	(1.07)	(1.22)	(2.18)
N Workers × Years	3,581,151	2,226,392	1,849,704
N Workers × Events	748,222	676,422	382,903
N Unique Workers	480,947	432,810	242,009
N Events	380	380	380

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. $^{*}p < 0.05$, $^{**}p < 0.01$, $^{***}p < 0.001$.

Appendix

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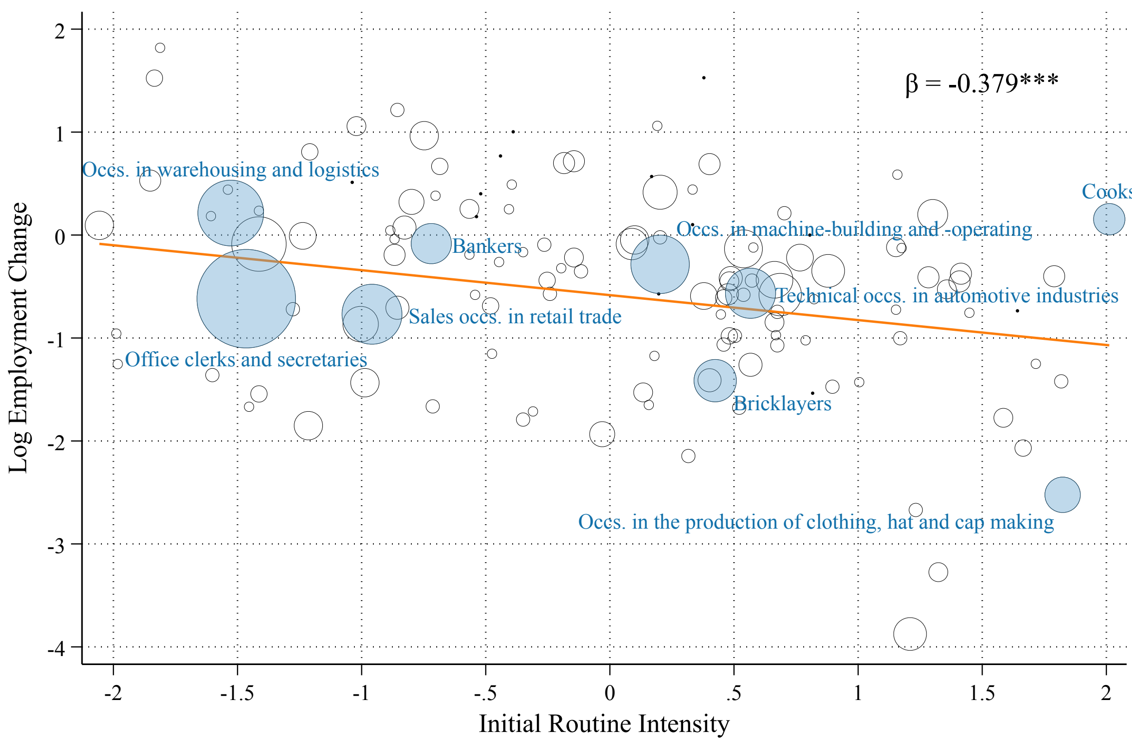
A Appendix figures and tables

Figure A1: 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.

Figure A2: Changes in Routine Task Intensity in All Curricula, 1976–2021

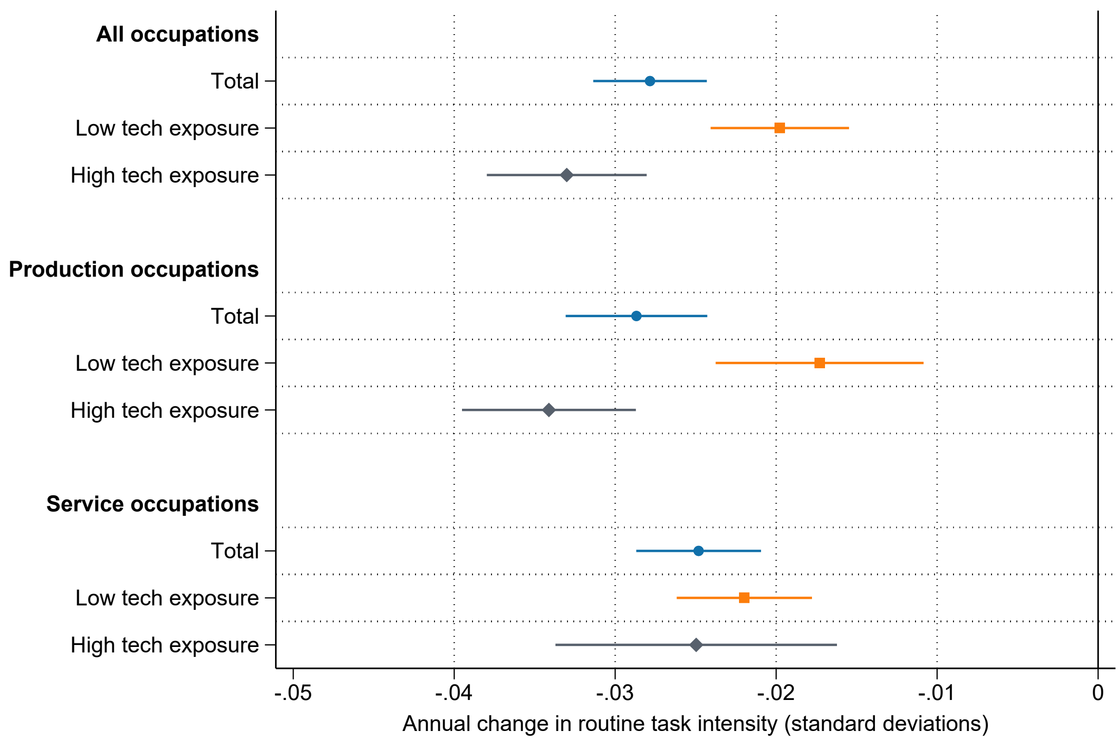


Figure reports coefficients on a linear timetrend, from a regression of routine task content in vocational training curricula (see equation (4)), for all curricula over 1976–2021. Horizontal lines reflect 95% confidence intervals. High tech (low tech) defined as curricula with an initial digital technology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

Figure A3: Changes in Digital Technology and Social Skill Use in All Curricula, 1976–2021

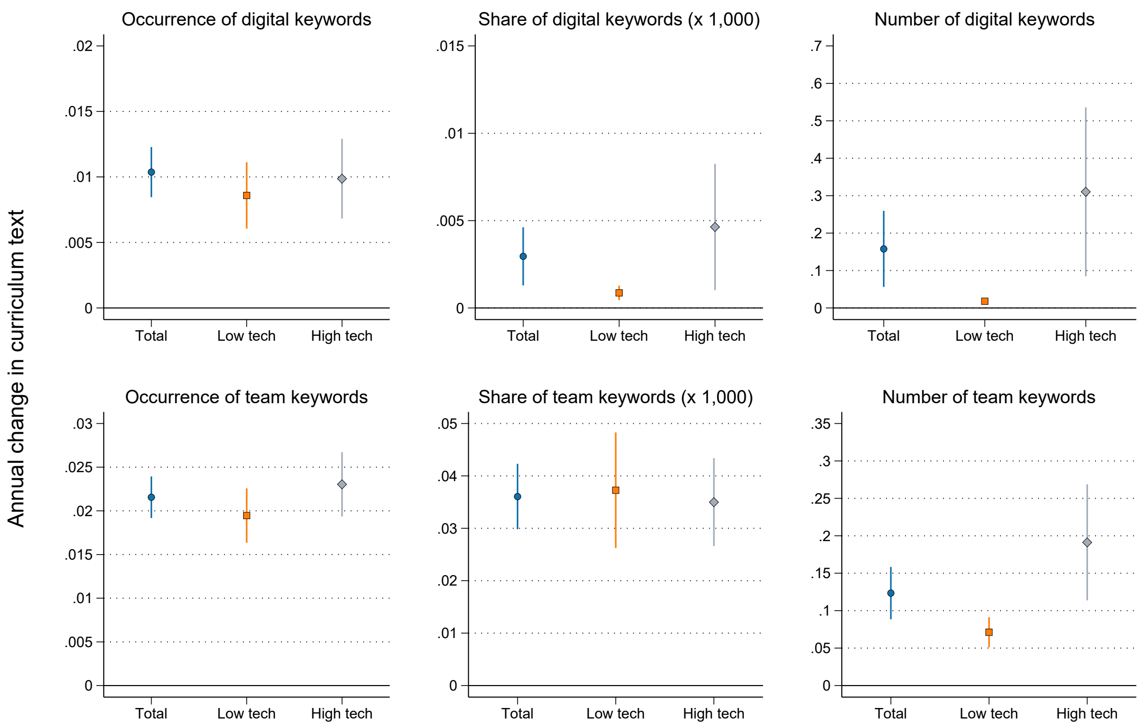


Figure reports coefficients on a linear timetrend, from a regression of keyword occurrence, keyword shares, or keyword counts in vocational training curricula (see equation (4)), for all curricula over 1976–2021. High tech (low tech) defined as curricula with an initial digital technology exposure above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

Figure A4: Impact of Curriculum Updates on Annual Days Employed

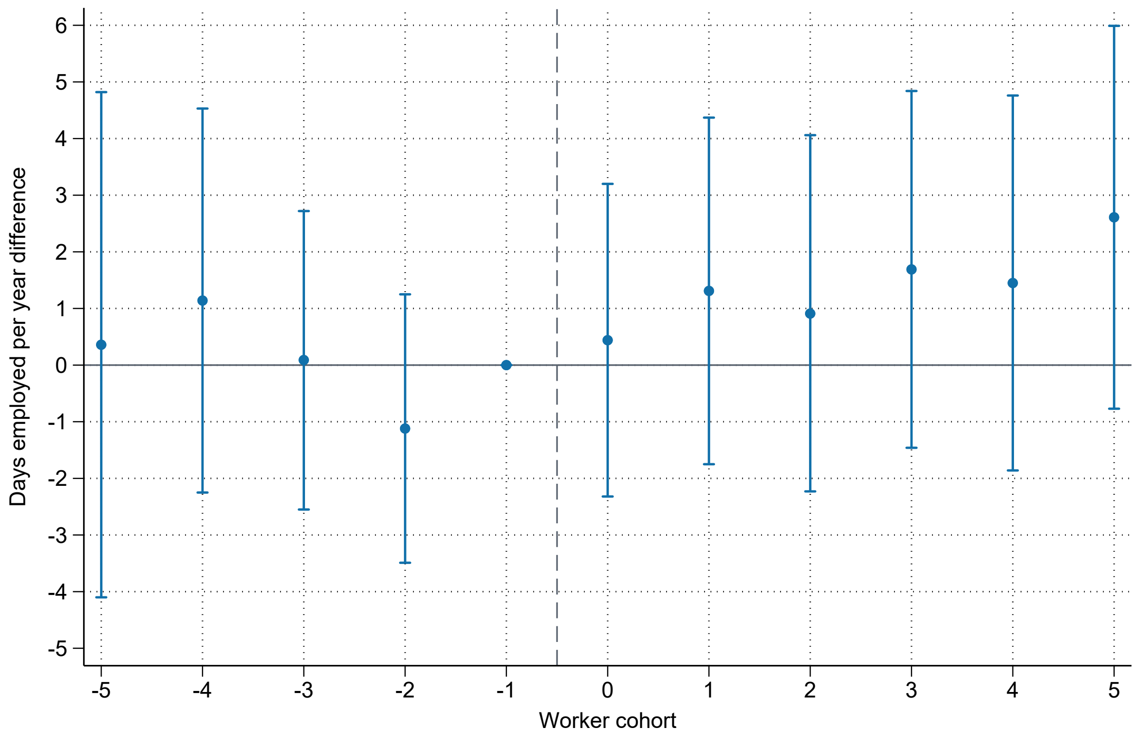
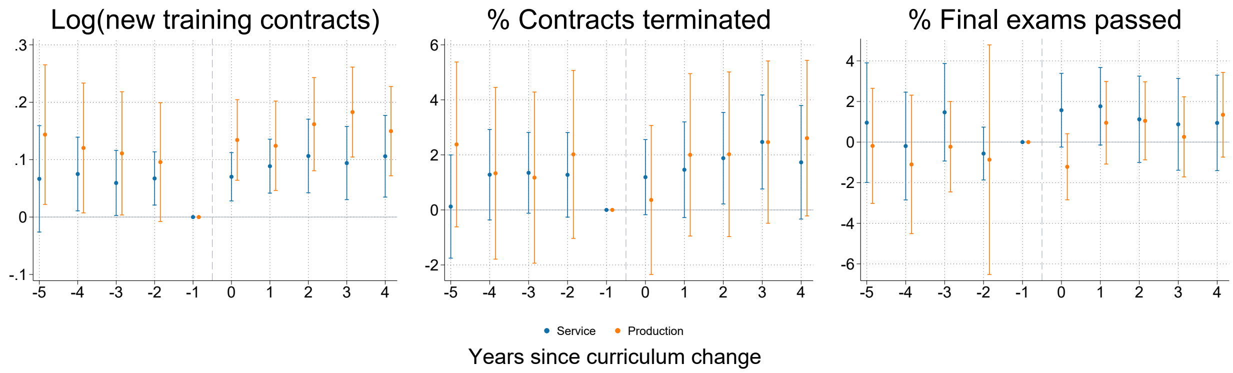


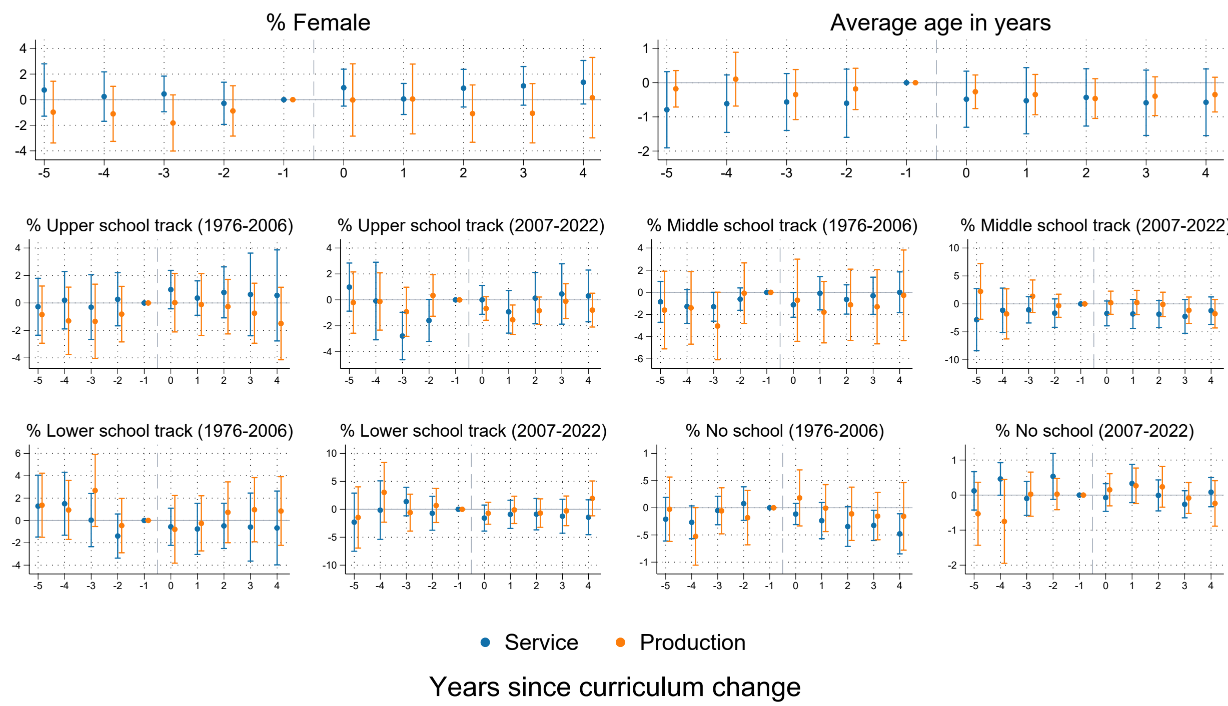
Figure reports stacked difference-in-differences estimates of equation (5), and 95% confidence intervals. Cohort 0 is the first cohort with the new curriculum; cohort -1 is the reference category. Individuals are included up to five years after graduation. Standard errors clustered at the level of training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

Figure A5: Apprenticeship Number and Composition Before and After Curriculum Updates – Production versus Service Occupations

A. Apprenticeship positions



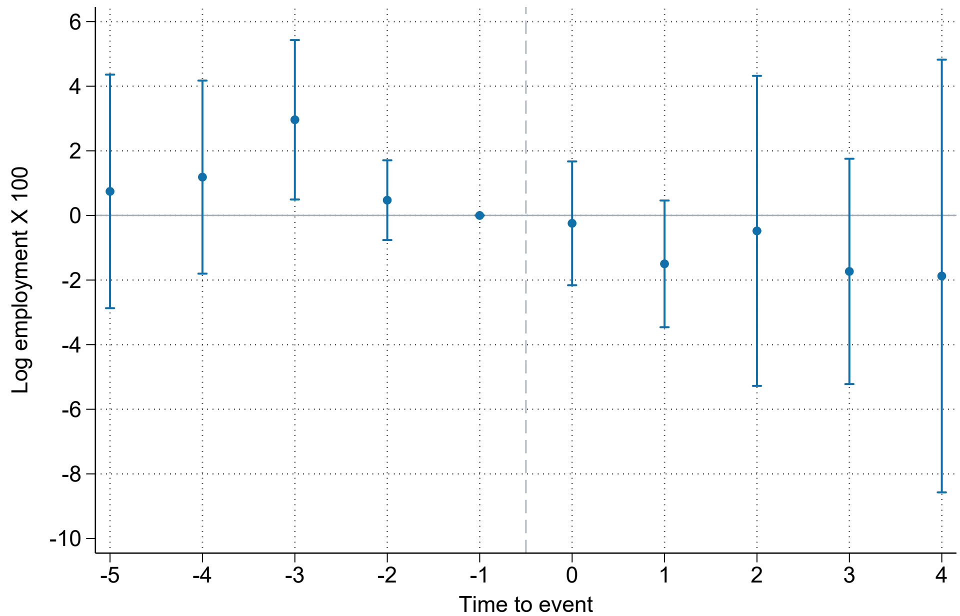
B. Trainee composition



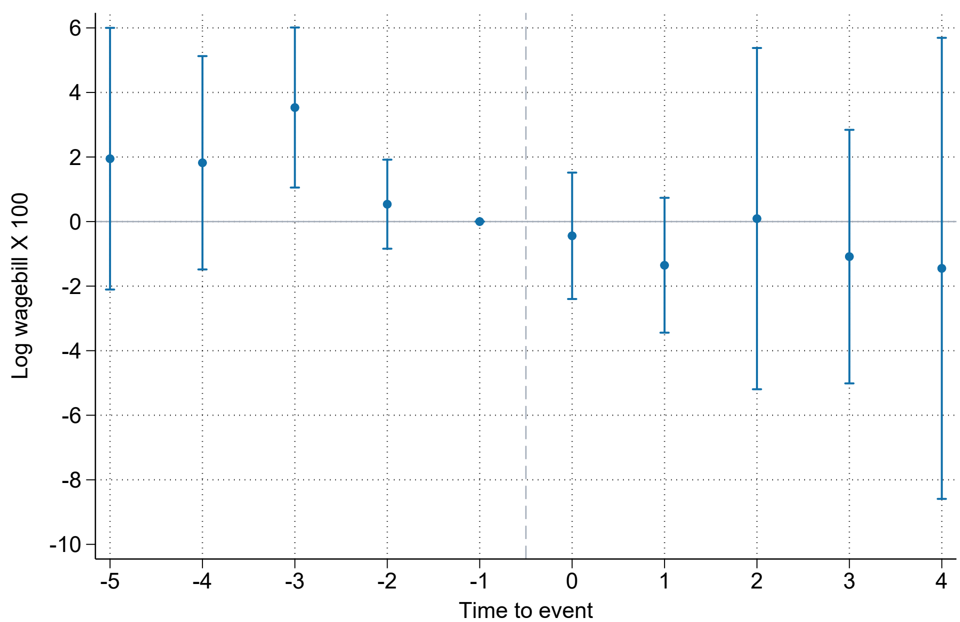
Stacked difference-in-differences estimates of curriculum updates on apprenticeship positions and composition comparing occupations with curriculum updates to occupations without updates, over 1976–2022. Based on 223 updating events in production occupations and 94 updating events in service occupations. N=39,180 for production occupations and N=18,565 for service occupations. 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. 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). % final exams passed available from 2010 onward; % female available from 1993 onward; average age in years available from 2007 onward.

Figure A6: 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.

Table A1: 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 A2: 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 A3: 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 A4: 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 A5: 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.

Table A6: 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 A7: 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 A8: 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 A9: 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 A10: 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 A11: 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

Table A12: Descriptives of Vocationally Trained Labor Market Entrants, Stacked Sample

	Treated			Control		
	Mean (1)	SD (2)	Median (3)	Mean (4)	SD (5)	Median (6)
Age	23.33	2.98	23.00	23.62	3.26	23.00
Year of birth	1976	10.16	1977	1978	9.47	1980
Female	0.33	0.47	0.00	0.48	0.50	0.00
Daily wage (euros)	71.89	30.47	73.13	69.10	31.10	69.80
Annual daily wage growth	0.33	4.16	0.07	0.38	9.25	0.07
Years of training	2.88	0.54	2.91	2.83	0.51	2.89
Typical years of training	3.07	0.41	3.00	3.00	0.34	3.00
Annual days employed	270.19	137.51	365.00	274.25	133.73	365.00
Annual labor earnings	18,958	13,830	19,303	18,399	13,485	18,228
Firm size	637.39	2,915.64	47.00	468.74	2,266.34	37.00
N unique workers		379,537			149,160	

SIEED sample, dataset stacked in event time as described in Section 4.1. 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 A13: Log Daily Wage Effects of Curricula Updates by Post-Training Year

	Post-training year:				
	Year 1	Year 2	Year 3	Year 4	Year 5
Treated × Cohort	(1)	(2)	(3)	(4)	(5)
-5	0.07	0.11	1.01	0.57	-1.95
	(1.56)	(1.10)	(1.10)	(1.10)	(1.07)
-4	1.59	1.26	0.82	2.03*	-0.10
	(1.01)	(0.93)	(0.97)	(0.98)	(0.95)
-3	3.18**	1.18	1.11	2.49*	0.50
	(1.07)	(1.02)	(1.11)	(1.01)	(1.15)
-2	1.51	1.04	0.07	1.44	0.33
	(0.97)	(0.92)	(0.96)	(0.93)	(1.01)
0	1.71	1.63	1.68	1.30	0.39
	(0.95)	(0.96)	(1.04)	(0.99)	(1.00)
1	2.06	-0.39	0.23	1.49	-0.17
	(1.13)	(0.98)	(0.97)	(1.07)	(1.14)
2	2.16*	2.63*	2.67*	2.85**	1.23
	(0.99)	(1.05)	(1.06)	(1.07)	(1.14)
3	4.25***	2.90**	3.30**	2.85**	3.10**
	(1.06)	(1.00)	(1.03)	(1.04)	(1.06)
4	3.04**	2.58*	3.64**	3.62***	1.49
	(1.10)	(1.08)	(1.17)	(1.10)	(1.23)
5	2.50	5.60***	2.55*	0.96	-0.03
	(1.37)	(1.20)	(1.18)	(1.14)	(1.17)
N Workers × Years	518,297	486,150	484,750	482,091	475,669
N Workers × Events	518,297	486,150	484,750	482,091	475,669
N Unique Workers	329,318	307,935	309,184	308,692	305,614
N Events	380	380	380	380	375

Stacked difference-in-differences estimates from equation (5), with separate regressions for each year post-training. 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 A14: Descriptives on Apprenticeship Positions and Trainee Composition

	Mean	SD	N
A. Apprenticeship positions			
Log(new training contracts)	5.78	2.13	57,771
% Contracts terminated	19.85	14.02	54,872
% Final exams passed	87.8	12.21	10,168
B. Apprenticeship composition			
% Female	32.24	33.91	37,079
Average age in years	18.88	2.52	14,603
% Upper school track (1976–2006)	15.57	19.62	30,276
% Upper school track (2007–2022)	21.22	22.32	12,008
% Middle school track (1976–2006)	31.36	17.57	30,276
% Middle school track (2007–2022)	36.59	15.62	12,008
% Lower school track (1976–2006)	35.8	23.85	30,276
% Lower school track (2007–2022)	34.38	25.4	12,008
% No school (1976–2006)	2.05	4.17	30,276
% No school (2007–2022)	2.48	3.06	12,008

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.

B 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 – Eastern 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).