Different degrees of skill obsolescence across hard and soft skills and the role of lifelong learning for labor market outcomes*

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This paper examines the role of lifelong learning in counteracting skill depreciation and obsolescence. We build on findings showing that different skill types have structurally different depreciation rates. We differentiate between occupations with more hard skills versus more soft skills. To do so, we draw on representative job advertisement data that contain machine-learning categorized skill requirements and cover the Swiss job market in great detail across occupations (from 1950-2019). We examine lifelong learning effects for "harder" versus "softer" occupations, thereby analyzing the role of training in counteracting skill depreciation in occupations that are differently affected by skill depreciation. Our results reveal novel patterns regarding the benefits from lifelong learning across occupations: In harder occupations, with large shares of fast-depreciating hard skills, the role of lifelong learning is primarily as a hedge against unemployment risks rather than a boost to wages. In contrast, in softer occupations, in which workers build on more value-stable soft skill foundations, the role of lifelong learning instead lies mostly in acting as a boost for upward career mobility and leads to larger wage gains.

Introduction

Technological change often leads to the disappearance of widely performed tasks and the obsolescence of once-valuable skills. The problem of skill obsolescence is amplified by macro-trends toward a more technology-driven economy (Brynjolfsson & McAfee, 2014) and an increasingly older workforce (OECD, 2006, 2019). Yet skills differ widely in their susceptibility to technological change. In addition, skills develop very differently with workers' age, which is a particularly important factor in aging societies. A growing literature

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argues that distinguishing between hard and soft skills as the two main constituents of the universe of skills (Deming, 2017) is crucial in this context: Hard skills (such as knowing how to operate a certain machine) do not age well, whereas soft skills (such as leadership ability) preserve their value over time (Backes-Gellner & Janssen, 2009; Deming & Noray, 2020).

Although skill obsolescence and depreciation have received increasing research attention, little is known about how to effectively counteract it. In the context of aging workforces (Bryson, Forth, Gray, & Stokes, 2020), lifelong learning is often proposed as a way of rebuilding human capital and creating a workforce that is ready for the future (Ainsworth & Knox, 2021; OECD, 2005a). Yet, given the different depreciation rates of different skill types, the contribution of lifelong learning and its different types to counteracting skill depreciation remains largely unexplored.

By examining the link between skill types, depreciation rates, and the need for lifelong learning, this paper brings together and contributes to the literatures both on skill obsolescence and lifelong learning (i.e., the benefits of training measures). While the literature on lifelong learning finds that training measures generally have positive effects on productivity and labor market outcomes (Backes-Gellner, Mure, & Tuor, 2007; Carruthers & Sanford, 2018; Frazis & Loewenstein, 2005; Georgiadis & Pitelis, 2016; Jacobson, Lalonde, & Sullivan, 2005; Konings & Vanormelingen, 2014), studies also find that these returns are very heterogeneous depending on educational level und individual worker characteristics (Coelli & Tabasso, 2019; Dostie & Javdani, 2020; Gauly & Lechner, 2019; Leuven & Oosterbeek, 2008; Schwerdt, Messer, Woessmann, & Wolter, 2012). The skill obsolescence literature finds that different skill types have structurally different depreciation rates (Backes-Gellner & Janssen, 2009; Deming & Noray, 2020; MacDonald & Weisbach, 2004; Neuman & Weiss, 1995). By combining these two literatures and shedding light on the impact of different skill depreciation rates, this paper provides new insights into why different workers benefit very differently from lifelong learning.

In particular, this paper examines how the relative importance of hard and soft skills in workers' occupations affect labor market returns to lifelong learning measures, that is, nonformal education measures as defined by the OECD (2005a) (Such lifelong learning measures are also often referred to as continuing education or continuous training; for brevity we use only "training" in the following.) To capture the skill types in occupations at a granular level, we draw on a large dataset of job advertisements (hereafter, "job ads") from Switzerland. For this data set, a machine-learning algorithm has categorized the skill requirements of each job ad by hard and soft skills. We link these occupational skill requirements to individual-level data that include detailed information on training participation. This wealth of information allows us to be the first to examine the link between hard (versus soft) skills, training participation, and its effects on labor market outcomes.

Drawing on skill-obsolescence theories (Kredler, 2014; Neuman & Weiss, 1995; Violante, 2002), we make two contrasting hypotheses. First, as hard skills are more likely to become obsolescent than soft skills given technological advances (Deming & Noray, 2020; MacDonald & Weisbach, 2004), we hypothesize that workers using more hard skills also have to rely more on training for counteracting skill depreciation and maintaining current productivity levels to ensure their employability. We therefore expect that, the more hard skills workers use, the larger the employment effects. Second, as soft skills preserve their value over time (Backes-Gellner & Janssen, 2009), we hypothesize that workers in occupations with more soft skills do not require training for counteracting skill depreciation and remaining at a certain productivity level. Instead, they can use lifelong learning to add new skills to their existing and stable skill portfolio and thereby gain in productivity. We thus expect that, the more soft skills workers use, the larger the wage gains and upward career mobility from training participation.

Based on job ad data from the Swiss Job Market Monitor (SJMM) (Buchmann et al., 2017), which includes a categorization of skill requirements with the help of a machine-learning algorithm, we empirically measure the hard and soft skill requirements of occupations. The algorithm precisely identifies words that represent the two types of skill requirements within job ad texts (Gnehm, 2018). Depending on the number of words describing hard versus soft skills, we determine where each occupation is located on a theoretical continuum ranging from fully hard-skill intensive (i.e., only hard skills) to fully soft-skill intensive (i.e., only soft skills). Specifically, we calculate the percentage of words describing hard skills in the sum of words describing hard and soft skills for the job ads for each occupation. For simplicity, we refer to the continuum as "hard-soft skill spectrum" and to occupations as being "harder" ("softer") in the sense of requiring relatively more hard (or soft) skills. For example, according to our empirical measurements, information technology (IT) occupations are the hardest occupations, which our measurement locates at 0.72 on the hard-soft skill spectrum (i.e., 72% of the skill requirement words represent hard skills). In contrast, the softest are hospitality occupations, which our measurement locates at 0.41 on the hard-soft skill spectrum (i.e., only 41% of the skill requirement words represent hard skills).

We match individual workers' data from the Swiss Microcensus of Continuing Education (SMCE)[1] to the locations of their occupations on the hard-soft skill spectrum. The SMCE contains detailed information on the educational, occupational, training choices (including training content), and labor market outcomes of about 18,500 individuals. The combination of the two data sources enables us to examine the link between hard versus soft skills, training participation, and its labor market returns,

Our regression results reveal different tradeoffs in the returns to skills and training along the hard-soft skill spectrum: In harder occupations, while workers receive on average higher

[1] The SMCE is provided by the Swiss Federal Statistical Office, 2019.

wages, their employment probability deteriorates sharply without any training. Training has positive employment effects, and—in harder occupations—these positive employment effects of training are further amplified. These larger effects are mainly driven by older workers who participate in hard-skill training. Lifelong learning likely helps these workers to rebuild the human capital they lost in fast-depreciating hard skills and to keep productivity at a certain level required for employment. Put differently, in harder occupations, training mostly functions as a hedge against the unemployment risks caused by fast-depreciating hard skills.

In contrast, in softer occupations, which have on average lower wages but higher long-term employment probabilities, training leads to amplified wage gains rather than greater employment effects, irrespective of the training content.[2] As softer occupations typically suffer less from skill obsolescence, workers likely add new skills to their existing and value-stable skill portfolio. Consequently, this addition of new skills increases workers' productivity levels in softer occupations, in turn boosting wages and unlocking better career prospects.[3]

In our data, we find further supportive evidence that productivity maintenance for harder occupations and upward career mobility for softer occupations underlie these empirical patterns. We draw on survey information in the SMCE on the subjectively perceived motivations for and the experienced benefits of participating in training. Our results show that, in harder occupations, training participants more often mention "technological change" as the motivation for their participation. In contrast, in softer occupations, training participants more often mention "promotion" as the benefit.

One potential concern with our findings is that self-selection into occupations along the hard-soft skill spectrum (either by initial occupational choice or by switching occupations) and into training participation may underlie our empirical patterns. We provide evidence from

[2] As we want to separate employment effects from *direct* wage effects, we examine wages conditional on employment.

[3] In harder occupations, training can also lead to wage gains, however, only if workers combine hard-skill with soft-skill training, which as a combination allows for escaping the environment of high skill depreciation rates (e.g., by bringing workers onto a career track for becoming "intrapreneurs" or technical managers) and thus enables long-run productivity increases.

several robustness checks. Analyzing "switching jobs" as motivation for training participation, we show that such motivational patterns do not differ between harder and softer occupations. Moreover, based on Leuven and Oosterbeek's (2008) restricted comparison-group method, we find that further filtering out selection into occupations and training leads to empirical patterns similar to our main findings.

The remainder of the paper is organized as follows. In the second section, we describe our theoretical framework, summarize prior empirical findings, and derive hypotheses on how the different depreciation rates of hard and soft skills affect the returns to training. In the third section, we then give our data sources, describe how we measure hard and soft skills, and explain our empirical approach. In the fourth section, we present our main results, which are then followed in the fifth sections by additional robustness checks on the validity of our findings, their underlying mechanisms, and the role of selection. In the sixth section, we conclude with a summary of our findings and policy implications.

Theoretical and Empirical Considerations and Hypotheses

Skill-obsolescence theories aim at explaining how changes in the nature and value of skills shape career and earning dynamics throughout the working life. For skills, value loss can take two major forms: internal depreciation (i.e., a worker's loss of mental and physical strength) and external depreciation (e.g., a lower valuation of skills, stemming from a changing technological environment) (Grip & van Loo, 2002; Neuman & Weiss, 1995; Rosen, 1975). For a better understanding of the mechanisms underlying participating in training and the labor market returns to it, differentiating between skill types is particularly useful within the context of external depreciation (Becker, 1980; van Imhoff, 1989). The reason is that while individuals obtain a large part of their skills during their initial formal education, the technological environment keeps changing—and, therefore, as these skills age, so does their value.

While those individuals with newer skills (i.e., more updated ones needed for new technologies) can reap momentary benefits, those with older skills (i.e., outdated ones) face continuously increasing skill obsolescence. Theoretical and empirical approaches show that the appearance of new technologies leads to an increased wage dispersion and that acquiring the skills needed for those technologies is associated with wage growth (Violante, 2002). Similarly, working in young establishments (e.g., start-ups) that use new technologies yields the highest tenure premiums as long as these technologies are at the innovation frontier (Kredler, 2014; Violante, 2002). In contrast, workers with older skills face increasing skill obsolescence. Generally, most skills lose value as they age; therefore, the more of these skills workers have, the greater the total loss of value. Neuman and Weiss (1995) show that workers with higher education levels and thus a greater amount of skills are more affected by skill obsolescence (for similar effects, see also MacDonald & Weisbach, 2004, and Lovász & Rigó, 2013).

Skill obsolescence depends not only on the amount of skills but also strongly on the skill type. While some skills age better, others rapidly lose their value. Theoretical models of skills (Deming, 2017) argue that the universe of skills can be broadly divided into two key elements: hard skills (cognitive skills) and soft skills (social skills and noncognitive skills). Backes-Gellner and Janssen (2009) show that soft skills, which are often experience-based (e.g., negotiating skills), preserve their value over time, as seen in workers with such skills exhibiting steeper age-earnings profiles (as opposed to flatter ones). In contrast, hard skills—which are mainly based on knowledge, not experience (e.g., using particular machines or certain programming languages)—quickly lose their value over time, as implied by flatter age-earnings profiles but higher starting levels. Put differently, while hard skills enable better initial career-starting conditions such as higher wages, they also lead to more skill obsolescence and less favorable earnings dynamics later in the working life. This finding that hard skills do not age well appears also in Deming and Noray (2020), who show that particularly occupations in science, technology, engineering and mathematical (STEM) fields exhibit flatter age-earning profiles and that workers in these fields more often sort out of these occupations. In sum, as skills age, they tend to lose value. This principle applies particularly to hard skills, which are fast-depreciating, in turn negatively affecting earning dynamics and incurring substantial economic costs for both firms and workers.

Training participation is often proposed as the best way of updating older skills, with studies showing that it has various economic returns such as improved productivity, greater employability, and sizable increases in wages (Backes-Gellner, Mure, & Tuor, 2007; Carruthers & Sanford, 2018; Frazis & Loewenstein, 2005; Georgiadis & Pitelis, 2016; Jacobson, Lalonde, & Sullivan, 2005; Konings & Vanormelingen, 2014). Training also has wider returns such as greater job satisfaction and gains in social capital, e.g., from a larger social network (Ainsworth & Knox, 2021; Balatti & Falk, 2002; Georgellis & Lange, 2007; Ruhose, Thomsen, & Weilage, 2019). Nevertheless, other studies show that these various returns are heterogeneous and strongly depend on workers' educational and professional backgrounds (Coelli & Tabasso, 2019; Gauly & Lechner, 2019; Leuven & Oosterbeek, 2008; Schwerdt, Messer, Woessmann, & Wolter, 2012).

One important source of heterogeneity is job content, which plays a considerable role in training participation and its effects. Workers in nonroutine jobs are more likely to participate in training (Görlitz & Tamm, 2016b; Mohr, Troltsch, & Gerhards, 2016), and training participation skews workers' job tasks toward more nonroutine analytical ones (Görlitz & Tamm, 2016a). These task changes further depend on the skill learned during training, with training in "communication and soft skills" having particularly strong effects and often leading to new tasks in nonroutine interactive fields (Tamm, 2018).

Given these theoretical and empirical findings on skill obsolescence and training, we derive hypotheses on the role of different skill types and their different depreciation rates. We approach the returns to training from the perspective of the skills that workers already have and use in their current occupation. In particular, we take the dichotomy of hard and soft skills and their fundamentally different exposure to skill obsolescence as the foundation for our analysis of occupational skills, and explicitly distinguish between these two types. Moreover, we take into account the heterogeneity in the labor market returns to training.

We expect hard and soft skills to play a major role in the returns to training, leading to patterns of heterogeneous returns. We hypothesize that, in occupations with many fast-depreciating hard skills, workers constantly need to rebuild the lost part of their human capital and—given high depreciation rates—cannot increase their productivity far beyond their current level. We therefore expect that occupational hard skills amplify employment effects, functioning as a hedge against the unemployment risks of fast-depreciating hard skills. In contrast, we expect occupational soft skills to amplify wage gains because they provide workers with a value-stable skill foundation to build on through training participation. We hypothesize that, in occupations with many soft skills, training leads to productivity gains and functions as a boost for upward career mobility.

To test these hypotheses, we need detailed information on occupational hard and soft skills, training choices and content, and labor market outcomes. The next section presents and discusses our data sources and methods.

Data and Methods

Swiss Job Market Monitor.—To measure the hard and soft skills that occupations require, we draw on job ad data. Job ads capture firms' skill needs and allow us to identify which occupations require which skills and how many of them. The use of words in job ads (i.e ., the type and amount) is tied to a firm's economic decision: Including additional words in the text of (newspaper) job ads incurs a cost for the firm advertising the vacancy.[4] Firms therefore tend to mention skills only if these skills are actually important for the announced job position.

We use job ad data from the Swiss Job Market Monitor (SJMM), which contains a sample of 90,700 job ads from Switzerland and is representative for the entire Swiss job market (Buchmann et al., 2017).[5] Its data is high quality because the SJMM team hand-typed the text of the job ads.[6] Moreover, the SJMM team manually coded the key characteristics of job ads for their own research purposes. For each announced job position, this manually captured information contains, among other things, the occupational title and its classification according to the Swiss Standardized Classification of Occupations (SBN-2000). We use this classification to track skill requirements over time, both within and across occupations.

To measure occupational hard and soft skills, we draw on the results of a supervised machine-learning text classifier (i.e., we use the results from Gnehm, 2018, who applied this method to the SJMM job ads). The classifier assigns the words of each job ad in the SJMM to one of eight categories, called "textzones." Given strong norms for how firms structure job ads—i.e., starting with a firm's introduction, mentioning the job title, and then describing the job content and the required skills—these textzones reflect the typical structure of job ads. We use the textzones for hard and soft skills, which are categorized according to well-established definitions of these two skill types (Salvisberg, 2010). The hard-skill textzone includes specific requirements for the "hard" knowledge needed for the job position (e.g., knowledge of the programming language "Java"). In contrast, the soft-skill textzone includes words describing

[4] From 1950-2000, the SJMM contains only newspaper job ads. From 2001, it also includes online job ads.

[5] From 1950 to 2019, the SJMM has covered the job market annually. The universe of job ads sampled by the SJMM is the total volume of job ads published by relevant advertising media at a given point in time. The SJMM adjusts the selection of advertising media to correspond with the advertising practice (e.g., the rising importance of online advertising). The SJMM collects its data by drawing stratified random samples from advertising media, with a stratification of newspaper media depending on region and circulation, website media depending on sectors and size of the firm, and job portal media (exhaustive sampling) depending on job categories.

[6] Job ad data used in earlier studies often does not precisely capture the full text (e.g., Atalay, Phongthiengtham, Sotelo, & Tannenbaum, 2018). The SJMM data captures all words in each job ad.

the required soft skills (e.g., being a “team player”). The words in these textzones represent the hard and soft skills needed for occupations and are strongly correlated with external measures of skill requirements.[7]

As the textzone classification is at the word level, we use the number of words in the hard-skill and soft-skill textzones to capture how hard (versus soft) occupations are. We position each occupation on a continuum ranging from fully hard-skill-intensive to fully soft-skill-intensive: the hard-soft skill spectrum. The location on the hard-soft skill spectrum then captures whether occupations require relatively more (less) hard skills, i.e., the occupation is harder (softer). To determine skill requirements at a given time, we use job ads from the two years before and after that point in time and aggregate the number of hard- and soft-skill words at the 2-digit level of the Swiss Standardized Classification of Occupations.[8] This procedure allows us to reconstruct the skills that the current occupation of workers requires and enables us to capture changes in these requirements within occupations over time (i.e., we exploit not only variation in requirements across occupations but also across time).[9]

To determine the location of each occupation on the hard-soft skill spectrum, we divide the number of words representing hard skills by the sum of words representing both skill types (i.e., the sum of words for hard and soft skills).[10] Formally, we apply the following formula to

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[7] Using external data of expert assessments on the skill requirements of vocational occupations (“Anforderungsprofile”) (Goetze & Aksu, 2018), we check for the external validity of using words from job ads to measure skill requirements. We find that the respective expert assessments are strongly correlated with the number of both soft-skill and hard-skills words in vocational occupations.

[8] Using the 2-digit level of the Swiss Standardized Classification of Occupations ensures a sufficient number of observations for examining changes in skill requirements over time even for smaller occupations. As an alternative we also constructed a version of skill requirements at the next lower 3-digit level but pooled the requirements over recent years (2009-2018). We find that the 2-digit and 3-digit measures are highly correlated (r=0.72), showing that the variation of skill requirements at the lower occupational level reflect itself strongly also at the next higher occupational level.

[9] Some occupational groups are too small and have too few job ads (i.e., less than 50 ads in the four-year bins) for us to make meaningful inferences from their job ads on the required hard and soft skills. We exclude these occupations (e.g., agricultural) from our sample.

[10] The reason that we chose a relative measure of hard-skill and soft-skill words over their absolute measures is that the relative measure allows us to later show our results in an empirically more concise and interpretable framework. Absolute measures for both hard and soft skills effectively double the number of interactions required in a regression framework, making interpreting the results increasingly difficult. However, one potential concern with relative measures is that it leads to an information loss on the absolute dimension of skill requirements. In other words, occupations may require not only more of one or the other skill but actually more of both. Using alternative measures that account for this dimension (such as the absolute number of hard- and soft-skill words or the percentage of the hard- and soft-skill words in the total text) does not change our results in a meaningful way.

the determine the location of occupation o in microcensus wave t on the hard-soft skill spectrum:

$$HardSoft\_SkillSpectrum_{o,t} = \frac{Hard\_Skill\,Words_{o,t}}{Hard\_Skill\,Words_{o,t} + Soft\_Skill\,Words_{o,t}} \quad (1)$$

The hard-soft skill spectrum ranges between 0 and 1, with occupations requiring only soft skills at 0 (at one end of the spectrum) and occupations requiring only hard skills at 1 (at the other end). The measure effectively captures the percentage of hard skills, i.e., the relative importance of hard skills compared to soft skills.

[Figure 1]

Figure 1 shows how selected occupations (2 digit-level and as average across waves) fall on the hard-soft skill spectrum (a comprehensive table with the location of all occupations can be found in Table A1 in the Appendix). The ordering of occupations aligns with skill measurements in similar contexts (Backes-Gellner & Janssen, 2009; Deming, 2017) and confirms economic intuition: IT occupations and engineering occupations focus the most on hard skills (with a value as high as 0.71 on the spectrum) and occupations in the hospitality industry and housekeeping focus the most on soft skills (with a value as low as 0.42 on the spectrum). Having measured how hard (soft) occupations are, we then can capture the training participation and labor market outcomes of the individuals in these occupations.

Swiss Microcensus of Continuing Education.—To capture lifelong learning and its labor market returns, we use individual-level data from the Swiss Microcensus of Continuing Education (SMCE). The great advantage of the SMCE is that it contains highly detailed information on the educational careers and training choices of individuals. The SMCE currently consists of two waves that survey the population in Switzerland, taking place in 2011 and 2016 and containing about 12,000 observations in each wave.[11] The SMCE is representative for (working and non-working) individuals aged 15-74, who live in Switzerland. As individuals were randomly sampled for each wave, the data constitutes a repeated cross-section.

Lifelong learning describes the choice to continue education outside the formal education system and throughout a worker‘s career (Walker, 2009). It is often proposed as a way to rebuild human capital (OECD, 2005a). For participation in lifelong learning, to which we refer simply as "training participation," we consider for each individual all choices to participate in nonformal education measures. We follow the OECD definition of nonformal education measures ("nicht-formale Bildung") as courses, seminars, workshops, and private teaching measures that take place outside the formal education system and do not lead to a formal educational degree (OECD, 2005b). This definition includes training of both at and off the workplace. The individuals in the SMCE state whether they had participated in such training measures in the last 12 months (yes/no).[12] We use this binary outcome to capture training participation very broadly, without making any ad hoc assumptions on the relevance of certain training types.

In addition to training participation (in general), the SMCE also contains in-depth information on the content of each training measure. To complement the broader perspective of general training participation with a more fine-grained perspective, we also examine the training content—the skills that workers acquire when participating in training. Based on skill-obsolescence theories, we expect certain labor market returns to materialize only in certain combinations of occupational skills and skills learned during training. These more specific

[11] The Swiss labor market experienced similar macroeconomic conditions in 2011 and 2016, with unemployment rates of 2.8% and 3.3% respectively (State Secretariat for Economic Affairs, 2021).

[12] The SMCE asks for training participation only in the last 12 months (instead of the entire training history) because, in the context of nonformal education, participants may easily forget participation, timing or content of training measures far in the past. Limiting questions to the recent training history ensures a high quality of survey answers on the features of training participation.

predictions allows us to use the training content information as an additional way of examining the credibility and interpretations of our results.

To make the connection between occupational skills and skills learned during training, we again build on the dichotomy of hard and soft skills and apply their definitions to the training content. For each training measures, the SMCE provides a categorization of the content into one of 15 different training-content topics, which we use to group training measures more broadly into hard-skill, soft-skill or mixed training. We assign training measures with informatics, finance, production, and science as training content to hard-skill training, because they provide skills that are directly needed in production (i.e., such as how to operate certain machinery or use certain software). In contrast, we assign training measures with management, personality, and language as training content to soft-skill training, because they provide skills that are mainly required for communication and the coordination of tasks (i.e., interpersonal skills such as how to lead a group or work in a team).[13] As some training measures contain a mix of both hard- and soft-skill components (which is the case of training measures in health and teaching), we assign them to a category of mixed training measures. Finally, we assign the remainder of course content—training measures with art, sports, and household as the content—to an extra category of skills unrelated to work. We use this unrelated category as an additional "placebo-type" check.

To link occupational skills to training participation and content, we use information on the current occupation of individuals from the SMCE. To ensure a consistent sample of individuals throughout our analyses, we restrict our sample in the following ways: First, we include only individuals sharing information on their current occupation, because only these

[13] In addition to this narrow definition of hard and soft skills, we also use a wider definition as a robustness check. This wider definition assigns all production-type skills to hard skills and only purely coordination/communication-type skills to soft skills. In this definition, hard skills are very widely defined, so that also training measures in health and teaching fall under hard skills. This alternative (wider) definition yields empirical patterns very similar to that of the narrower one.

individuals can be matched to the skills of their current occupation.[14] Second, as we focus on the labor market patterns of older individuals whose skills are aging and prone to skill obsolescence, we concentrate on individuals who are past their initial formal education. We examine individuals between the age of 30 (to ensure a substantial distance to the initial formal education) and 64 (the retirement age for women in Switzerland).[15] Third, to ensure that outliers in both training measures and labor market outcomes do not distort our empirical findings, we exclude the top and bottom percentile of labor incomes (conditional on individuals being employed) and the top percentile of duration and spending on training.

[Table 1]

Table 1 (Panel A) displays the most common features of training for our sample. The majority of individuals (71%) participate in training measures, with most of training being work-related and employer sponsored. On average, individuals participated in 1.86 training measures and spent a total of 531 Swiss Francs (roughly $585) for these measures (as individual costs and not accounted for employers' costs) in the past 12 months. Table 1 (Panel B) displays more in-depth characteristics of training measures: Participation in hard-skill training (38%) is at similar levels as soft-skill training (30%).[16] The average training duration is 25 hours, and average training costs are about 206 CHF (roughly $310) (costs to the individual). These descriptive statistics show an active participation in training and substantial variation in the type of training (i.e., hard-skill training and soft-skill training).

To assess the labor market returns that accompany training participation, we examine how wages and employment probability, as two key outcomes, change along the hard-soft skill spectrum and in response to training participation. The SMCE offers information on the

[14] For unemployed individuals, we use the last occupations that they have worked in.

[15] The SMCE targets the entire population (not just the working population) and contains survey information on individuals aged 15 to 74 years.

[16] About 14% of individuals participated in both hard-skill and soft-skill training.

employment status (employed versus unemployed) and yearly labor income of individuals. We calculate the yearly labor income as a full-time equivalent (for simplicity, hereafter "wage"), which adequately accounts for part-time employment. Table 2 displays summary statistics for the labor market outcomes (employment and wages), personal characteristics (age, gender, nationality, and marital status), and formal education backgrounds (highest educational degree) of individuals in our sample. With this sample, we more deeply examine the empirical patterns of occupational skills, training participation, and labor market returns.

[Table 2]

Estimation.—To empirically examine the role of occupational hard and soft skills in the labor market returns to training participation, we estimate a linear regression (linear probability) model. We estimate the following equation:

$$LaborMarketOutcome_{i,o,t} = \alpha + K_{i,o,t} + FormEduc_{i,o,t} + \beta HS\_Spectrum_{o,t} + \gamma Train_{i,o,t} + \delta Train_{i,o,t} \, x \, HS\_Spectrum_{o,t} + \varepsilon_{i,o,t} \quad (2)$$

where $LaborMarketOutcome_{i,o,t}$ denotes our outcome of interest, that is, the employment status or log(wage) of individual i in wave t and occupation o. $HS\_Spectrum_{o,t}$ captures the position of the skills of occupation o in wave t on the hard-soft skill spectrum. $Train_{i,o,t}$ is a binary variable which takes a value of 1 for training participation in general (irrespective of the skills acquired) and 0 if the individual does not participate in training. The parameter of interest is δ, which captures how the location of the occupation on the hard-soft skill spectrum moderates the labor market returns to individual training participation ($Train_{i,o,t}$). $K_{i,o,t}$ is a set of individual characteristics available for both employed and unemployed workers, including gender, Swiss nationality, age (plus age squared), marital status, and the wave in which the individual was surveyed (2011 or 2016). $FormEduc_{i,o,t}$ denotes a set of dummy variables for the highest formal educational level that an individual acquired in the Swiss education system. Controlling for the formal educational background enables us to rule out the possibility that educational levels, not occupational skills within these levels, drive our results.

Results: Training Participation and Patterns of Labor Market Returns

Figure 2 depicts the broader empirical patterns of our main estimation results. It presents the predicted employment and wage levels, depending on training participation (whether workers participate in training or not) and the workers' occupational position on the hard-soft skill spectrum. Moreover, the figure displays the predicted marginal effects of training participation (at the mean of the other covariates).

[Figure 2]

In Panel A, the curve for the predicted employment probability shows that if workers do not participate in training, their employment probability deteriorates quickly when they use relatively more hard skills. At the very hard-skill end of the spectrum (70% hard skills), the employment probability without training is only about 93% on average (compared to 97% with training). However, training participation can counteract employment probability deterioration by helping workers sustain their employment probability at around 97% all along the entire hard-soft skill spectrum. The diverging employment curves demonstrate that—consistent with hard skills being more affected by depreciation and requiring constant maintenance—workers in harder occupations rely more on training for maintaining employability and experience higher employment effects.[17]

However, while on one hand workers in harder occupations suffer from deteriorating employment probabilities, on the other hand they experience higher wages on average. The rising wage curves in Panel B (both with and without training) show that workers in harder

[17] Given the high rate of depreciation for hard skills, we earlier hypothesized that workers in harder occupations are forced to update their skills more frequently. Consistent with this prediction, we find that, in harder occupations, workers are more likely to participate in training.

occupations earn on average higher wages than do workers in softer occupations. These findings illustrate an important tradeoff: In harder occupations, while workers receive higher wages, their employability deteriorates sharply without training. This tradeoff shows that, while hard skills are economically very valuable when kept up to date, they also can quickly lose their value when not maintained.

In contrast, in softer occupations, long-term employment probabilities are high, even without participation in training. In Panel A, the curve for the predicted employment effects of training shows that, for occupations mainly requiring more soft skills (*HS_Spectrum* < 0.50), the employment increase is not significantly different from 0 (with 90 percent confidence intervals). Finding that the employment probability is unaffected by training participation in softer occupations is consistent with soft skills preserving their value over time, i.e., being largely unaffected by depreciation. However, while workers in softer occupations experience more stable employment prospects, they also experience lower wages on average (Panel B), adding yet another factor to the overarching tradeoff between hard and soft skills and training participation.

Workers in softer occupations experience not only lower wage levels but also different wage effects. The predicted wage levels in Panel B demonstrate that, when workers use relatively more soft skills, the wage gap between those with training participation and those without widens, indicating increasing wage gains for softer occupations. The predicted marginal wage effects (Panel B) capture these increasing wage gains: While, for workers in the hardest occupations, training participation is associated with a wage increase of only about 7%, for those in the softest occupations the increase is about 17%.

Table 3 more closely quantifies the employment and wage effects that underlie these broader empirical patterns: Columns (1) and (2) report the estimated coefficients that capture how occupational skill types and training participation relate to employment and wages.[18] The parameter of interest is the interaction between training participation (*Train*) and the location of the occupation on the hard-soft skill spectrum (*HS-Spectrum*). For the better interpretability of our coefficients at the mean of other covariates, we use a z-standardized version of the hard-soft skill spectrum (i.e., transforming it to a variable with a mean of zero and a standard deviation of one).

[Table 3]

For the influence of occupational skills on employment effects, Column (1) shows that, given training participation, moving one standard deviation towards more hard skills on the hard-soft skill spectrum *increases* the employment effect associated with training (which, at the mean of the hard-soft skill spectrum, is 1.51%) by an additional 1.37 percentage points. In other words, a one standard deviation move effectively almost doubles the employment effect (1.51% + 1.37% = 2.88% as total effect, which is jointly significant at the one-percent level). A one standard deviation move on the hard-soft skill spectrum corresponds to a change from occupations in banking and insurance to technical draftsman occupations. Moreover, Column (1) reveals that, while a move on the hard-soft skill spectrum toward more hard skills reduces the employment probability without training (by 1.32% per standard deviation), training participation fully cancels out this negative employment effect (i.e., the coefficients of *HS_Spectrum* and *Train x HS_Spectrum* fully offset one another).

For the influence of occupational skills on wage gains, Column (2) displays that, given training participation, a one-standard-deviation move on the hard-soft skill spectrum toward more hard skills *decreases* the wage effect by training participation (which, at the mean of the hard-soft skill spectrum, is an 11.42% wage increase) by 2.34 percentage points (11.42% -

[18] As an alternative approach, we use the 3-digit classification of the Swiss Standardized Classification of Occupations for constructing the hard-soft skill spectrum and find similar pattern of lifelong learning effects (see Table A2 in the Appendix).

2.34% = 9.08% total wage increase, which is jointly significant at the ten percent level). As hard and soft skills oppose one another on the spectrum, a move toward hard skills by one standard deviation implies a move away from soft skills by one standard deviation. From the perspective of the soft-skill end of the spectrum, the negative interaction coefficient implies that the softer the occupations, the higher the wage gains.

Taken together, these findings demonstrate that—in harder occupations—employment increases from training participation are amplified, while—in softer occupations—wage increases are amplified. As technological change rapidly depreciates the human capital of workers in harder occupations, these workers need to constantly rebuild the lost part of their human capital. Furthermore, given the high depreciation rates, these workers cannot increase their productivity far beyond their current level, meaning that training primarily functions as a hedge against unemployment by limiting the downward risk. In softer occupations, the patterns are distinctly different: As soft skills typically do not suffer from high depreciation rates, every newly learned skill from training participation adds to a value-stable stock of human capital, thereby enhancing productivity beyond current levels. This increased productivity allows workers in softer occupations to move up the career ladder and obtain higher wages.

Robustness Checks and Further Evidence

Different Training Types and Age Groups.—One potential concern with our main analysis is that the patterns we show are very broad and thus may reflect other underlying unobservable factors beyond occupational skill types. One way of dealing with this concern is to examine whether the empirical patterns hold against the predictions of skill-obsolescence theory at a more fine-grained level. We expect certain labor market patterns to materialize only in certain combinations in the occupational skills that workers already have, skills added through training measures, and exposure to skill obsolescence (i.e., workers' age). To empirically test these more granular predictions, we split our sample in two age groups (ages 30-47, "younger," and ages 48-64, "older") and differentiate between hard-skill training and soft-skill training.

One prediction of skill-obsolescence theories is that particularly older workers in harder occupations experience employability improvements. In general, older workers are more prone to skill obsolescence from technological change, because they acquired the larger part of their human capital (i.e., during their initial education) a longer time ago. As restoring human capital (i.e., updating older hard skills to newer ones) requires workers to actually match the skill deficit created by technology change, we expect the employment patterns in harder occupations to be driven mainly by older workers who participate in hard-skill training. This type of training provides older workers with the hard skills crucial for keeping their productivity above a certain level, even as they age. However, unless selection or unobservable factors play a major role, the stronger employment effects should not materialize as strongly for younger workers, because their skills are more up-to-date even without training. Consistent with these predictions, we find that, in harder occupations, employment effects arise mainly for older workers and are particularly strong for their participation hard-skill training (see Table A3 and Table A4 in the Appendix).[19]

Another prediction is that younger workers in softer occupations should see the largest wage gains, irrespective of the type of training. Younger workers in softer occupations are the least affected by skill obsolescence. Moreover, in softer occupations, new skills from training participation add to value-stable skill bundles, thereby likely increasing overall productivity (and wages). We therefore expect training to lead to upward career mobility and larger wage

[19] As an additional robustness check, we also apply the wider definitions of hard skills (all production-type skills) and soft skills (purely coordination/communication-type skills). With training measures previously categorized as "mixed" (health and teaching) now assigned to hard-skill training, this wider definition leads to a much greater occurrence of hard-skill training (i.e., most of those surveyed had participated in hard-skill training), making it statistically easier to detect effects for hard-skill training and more difficult for soft-skill training. Nonetheless, Tables A5 and A6 show that using this alternative wider definition has little impact on our overall empirical patterns.

gains, irrespective of the type of training in which workers participate, as long as the training adds work-related skills. Consistent with these predictions, we find that, in softer occupations, higher wage effects arise mainly for younger workers and for both, hard- and soft-skill training (see Table A3 and A4 in the Appendix).

Our more fine-grained analysis of age groups and types of training further reveals a path for workers in harder occupations toward larger wage gains from training participation. We find that the combination of both hard- and soft-skill training boosts the wage returns to training participation particularly in harder occupations. Our results show a strong positive and significant moderation effect from this specific combination of training measures (see Table A3 in the Appendix). This finding also resonates with theories of skill obsolescence: If workers in harder occupations participate only in hard-skill training, they will likely remain only in a track of "hard-skill specialists," who are under the constant pressure of high depreciation rates and therefore limited in improving their productivity or achieving upward career mobility.

However, by participating in the combination of hard- and soft-skill training, workers in harder occupations can instead likely move onto the career track of technical managers. This track enables them to escape the environment of high depreciation rates and move into a more stable environment, one that favors more general and balanced skills bundles. This new environment then likely enables upward career mobility and drives the higher wage effects for the combination of both hard- and soft-skill training. Another way to interpret this likely mechanism is that through this new track workers become intrapreneurs (e.g., technical managers), for whom a different and broader set of skills is important (see, e.g., Ahmad, Nasurdin, & Zainal, 2012; Antoncic & Hisrich, 2001, 2003).

Subjectively Perceived Motivations and Benefits of Training Participation.— Another potential concern with our main analysis and its interpretation is that motivations to rebuild human capital that was lost to technological change (productivity maintenance) and upwards career movements (promotions) may not be the actual drivers behind our empirical patterns. We handle this concern by drawing on additional data from the SMCE, which also asks individuals for a randomly selected training measure to self-assess (a) their motivations for participating in training and (b) their subjectively experienced benefits of that participation. Using simple yes/no answers, individuals choose from a predefined selection of potential training motivations and benefits, both of which can lie in their working or personal lives.

We find that, consistent with theories of skill obsolescence, mentioning technological change as the motivation for training participation ("due to organizational and technological change in the workplace") is much more common in harder occupations than in softer occupations (see Table A7 in the Appendix).[20] Of the various benefits that individuals can potentially receive from training participation, we find that individuals in softer occupations more frequently state "promotion" as their benefit (see Table A7 in the Appendix). These additional results further underscore the role of skill obsolescence in shaping the motivation for training participation and the benefits that it creates, such as maintaining productivity and or receiving promotions.

Role of Selection Effects.—Another confounding factor when assessing returns to training and exploring potential mechanisms behind these returns is that selection might play a potential role. In particular, one potential concern is that individuals with higher earning capabilities and better employment prospects might sort themselves into a certain direction on the hard-soft skill spectrum (either as initial occupational choice or by switching occupations) and, at the same time, more often into training participation. Given that we are mainly interested in the interaction between occupational skills and training participation, potential sorting along both of these dimensions constitutes the main threat to credibly interpreting our

[20] We also find that workers in harder occupations are more likely to participate in hard-skill training, likely reflecting the pressure from technological change for updating their fast-depreciating hard skills.

empirical patterns.[21] We show that selection along the hard-soft skill spectrum and into training participation (compared to no training at all) is only of minor importance for our findings.

As a first check for selections effects, we use training measures with themes in art, sport, and household as a placebo-type training category. Participation in this placebo category is likely correlated with important unobserved characteristics such as creativity, teamwork ability, self-organization, and overall mental agility. However, these training measures neither are directly work-related nor are directly linkable to hard or soft skills. This placebo category therefore enables us to check how selection along the hard-soft skill spectrum and into training might affect our findings (e.g., workers with better self-organization and better teamwork more often sorting into softer occupations, more often participating in training, and more often receiving promotions).

If selection on such unobservable characteristics plays a major role, we would expect it to show up as highly significant interaction effects between the location on the hard-soft skill spectrum and the placebo training category. However, we find insignificant interaction effects, with coefficients close to zero, for our labor market outcomes of interest (see Table A8 in the Appendix). Given these findings from the placebo-type training, we argue that selection along the hard-soft skill spectrum likely plays only a negligible role in our empirical patterns.

As a second check for selection effects, we focus on the potential nonrandom sorting of individuals into training participation and actively switching along the hard-soft skill spectrum (e.g., using training as a way for switching into another occupation). We examine how the motivation of "switching occupations" for training participation correlates with the location on the hard-soft skill spectrum. We find that "switching occupations" is largely uncorrelated with the location on the hard-soft skill spectrum (see Table A7 in the Appendix).

[21] Selection into training itself is not necessarily problematic. As we are interested in the interaction of both training participation and the role of the hard-soft skill spectrum, our interpretations rest on the absence of simultaneous selection along both dimensions.

Thus, active switching from particular occupations after training appears unlikely to be a confounder.

As a third check for selection effects, we follow Leuven and Oosterbeek's (2008) restricted comparison-group method. This method restricts the sample to workers who participated in training (treatment group) and those who were willing to do so but did not because they were hindered by circumstances (restricted comparison group). This restriction makes the group of nonparticipants more comparable to the treatment group in its unobservable characteristics, particularly for those characteristics influencing both training participation and labor market outcomes. The SMCE contains information on the nonparticipation of individuals such as the willingness to participate in training but being hindered by circumstances. Applying the restricted-comparison-group method to our sample greatly reduces the group of nonparticipants (only about 11% of the remaining sample are nonparticipants).[22] We analyze the empirical patterns for training participation in general and training participation differentiated by types of training and age groups in particular.[23] Our results show that similar empirical patterns of employment and wages along the hard-soft skill spectrum arise (albeit with smaller effect sizes) even when we use the comparison-group method, which greatly eliminates selection into training (see Table A9, A10 and A11 in the Appendix).

Conclusion

This paper analyzes the role of lifelong learning in counteracting skill obsolescence. As workers' occupational hard and soft skills have very different degrees of skill obsolescence and susceptibility to technological change, our analysis differentiates between these two skill

[22] As we do not have a category of hinderances that represent fully random circumstances, we follow the less restrictive version of Leuven and Oosterbeek (2008), which considers all nonparticipants who were willing to participate in training but did not (for internal and external circumstances) as the comparison group.

[23] The greatly reduced number of observations in the group of nonparticipants makes detecting effects difficult when examining returns to general training participation (all content). Our approach of distinguishing between hard- and soft-skill training allows for more variation when we examine the patterns of labor market returns to training participation.

types. Our results reveal distinctive patterns of labor market returns according to whether occupations are harder (versus softer) and demonstrate an important tradeoff in the labor market returns and training participation. While harder occupations are on average associated with higher wages, this wage advantage comes at the cost of decreased employment probabilities without training participation. The employment differences depending on training participation along the hard-soft skill spectrum are considerable: While for the softest occupations in our sample we find no statistical differences in the employment probabilities between workers who participate in training and those who do not, for the hardest occupations this difference amounts to up to 4% (which is substantial given the generally small average unemployment rate of 3% in Switzerland).

We attribute these strong employment differences to the different rates of skill depreciation, because training is crucial for ensuring employability in harder occupations, which rely on many fast-depreciating hard skills. While we find that hard skills are economically very valuable, given that they are associated with higher average wages at the beginning of a labor market career (as also shown by previous research; see Deming & Noray, 2020, and Backes-Gellner & Janssen, 2009), our results also reveal that these skills require constant maintenance through lifelong learning to keep workers' employability from deteriorating. Training participation likely helps workers in these harder occupations to keep up with rising technical requirements levels and thereby functions as a hedge against the most severe downside risk caused by fast-deprecating hard skills, i.e., unemployment risk. Consistent with workers having to constantly update and rebuild their depreciating hard skills, our findings show the employment effects are particularly strong for training measures that actually focus on hard skills and therefore match the skill deficit on the worker side, especially that of older workers. By showing this need to update hard skills to ensure employability for aging workers, our findings uncover a way of counteracting unfavorable career dynamics later in the working life.

In contrast, workers in softer occupations earn on average lower wages but experience higher longer-term employment probabilities. Moreover, in these occupations, training participation is accompanied by larger wage gains. As soft skills suffer less or not at all from skill obsolescence, workers in softer occupations likely add new and up-to-date skills to value-stable skill sets, thereby enhancing productivity beyond previous levels. Enhanced productivity then likely opens the door to promotions, with lifelong learning functioning as a boost for upward career mobility. This finding that soft skills affect career mobility is consistent with that of studies showing that soft skills have a particularly strong impact on job content after training participation (Görlitz & Tamm, 2016a; Tamm, 2018).

We also show supporting survey evidence for the two functions of training in the tradeoff between hard and soft skills: either being a hedge against unemployment risks in harder occupations or a boost for upward career mobility in softer ones. Consistent with these functions, workers in softer occupations more frequently rate promotion as the benefit of training participation, whereas workers in harder occupations more often mention technological change as the motivation for training participation.

The tradeoff along workers' hard and soft skills and training participation has important implications for public debates on designing and supporting training measures. Our findings suggest that, in harder occupations (e.g., technical fields), workers must constantly maintain their hard skills to keep their skill sets up to date and their employment prospects from deteriorating. When designing policy measures for mitigating highly negative labor market risks such as unemployment, policymakers need to focus on supporting measures that specifically update outdated hard skills.

Furthermore, our results suggest that—with many fast-depreciating occupational hard skills—the training of soft skills in addition to hard skills has substantial benefits. The results of our more fine-grained analyses indicate that the combination of hard- and soft-skill training allows workers in harder occupations to escape the environment of high depreciation rates, likely leading them to management-related positions (as intrapreneurs) with more balanced skills sets and higher wages. These findings suggest that additional benefits result from broadening skill bundles by building skills not only within existing skill types but more broadly between them. The benefits of broadening skill bundles may also translate into similar educational settings (formal or nonformal) in which skill depreciation plays a large role.

References

Ahmad, N. H., Nasurdin, A. M., & Zainal, S. R. M. (2012). Nurturing intrapreneurship to enhance job performance: the role of pro-intrapreneurship organizational architecture. *Journal of Innovation Management in Small & Medium Enterprises*, *2012*, 1.

Ainsworth, S., & Knox, A. (2021). “A bridge too far?” Ideas, employment relations and policy-making about the future of work. *Industrial Relations: A Journal of Economy and Society).* Advance online publication. https://doi.org/10.1111/irel.12295

Antoncic, B., & Hisrich, R. D. (2001). Intrapreneurship: Construct refinement and cross-cultural validation. *Journal of Business Venturing*, *16*(5), 495–527.

Antoncic, B., & Hisrich, R. D. (2003). Clarifying the intrapreneurship concept. *Journal of Small Business and Enterprise Development*, *10*(1), 7–24. https://doi.org/10.1108/14626000310461187

Atalay, E., Phongthiengtham, P., Sotelo, S., & Tannenbaum, D. (2018). New technologies and the labor market. *Journal of Monetary Economics*, *97*, 48–67. https://doi.org/10.1016/j.jmoneco.2018.05.008

Backes-Gellner, U., & Janssen, S. (2009). Skill obsolescence, vintage effects and changing tasks. *Applied Economics Quarterly*, *55*(1), 83–104.

Backes-Gellner, U., Mure, J., & Tuor, S. N. (2007). The puzzle of non-participation in continuing training: an empirical study of chronic vs. temporary non-participation. *Zeitschrift Für ArbeitsmarktForschung-Journal for Labour Market Research*, *40*(2/3), 295–311.

Balatti, J., & Falk, I. (2002). Socioeconomic contributions of adult learning to community: A social capital perspective. *Adult Education Quarterly*, *52*(4), 281–298.

Becker, G. S. (1980). *Human capital* (Vol. 3). University of Chicago press Chicago.

Brynjolfsson, E., & McAfee, A. (2014). *The second machine age: Work, progress, and prosperity in a time of brilliant technologies*. WW Norton & Company.

Bryson, A., Forth, J., Gray, H., & Stokes, L. (2020). Does Employing Older Workers Affect Workplace Performance? *Industrial Relations: A Journal of Economy and Society*, *59*(4), 532–562. https://doi.org/10.1111/irel.12265

Buchmann, M., H. Buchs, A.-S. Gnehm, D. Hevenstone, U. Klarer, M. Müller, . . . A. Salvisberg (2017). *Erhebung von Stelleninseraten 1950 - 2016 [Dataset]* (Universität Zürich - Philosophische Fakultät - Soziologisches Institut. Distributed by FORS, Lausanne, 2017).

Carruthers, C. K., & Sanford, T. (2018). Way station or launching pad? Unpacking the returns to adult technical education. *Journal of Public Economics*, *165*, 146–159.

Coelli, M., & Tabasso, D. (2019). Where are the returns to lifelong learning? *Empirical Economics*, *57*(1), 205–237.

Deming, D. J. (2017). The growing importance of social skills in the labor market. *The Quarterly Journal of Economics*, *132*(4), 1593–1640.

Deming, D. J., & Noray, K. (2020). Earnings Dynamics, Changing Job Skills, and STEM Careers. *The Quarterly Journal of Economics*, *135*(4), 1965–2005.

Frazis, H., & Loewenstein, M. A. (2005). Reexamining the returns to training functional form, magnitude, and interpretation. *Journal of Human Resources*, *40*(2), 453–476.

Gauly, B., & Lechner, C. M. (2019). Self-perfection or self-selection? Unraveling the relationship between job-related training and adults’ literacy skills. *PloS One*, *14*(5).

Georgellis, Y., & Lange, T. (2007). Participation in continuous, on-the-job training and the impact on job satisfaction: longitudinal evidence from the German labour market. *The International Journal of Human Resource Management*, *18*(6), 969–985. https://doi.org/10.1080/09585190701321112

Georgiadis, A., & Pitelis, C. N. (2016). The Impact of Employees' and Managers' Training on the Performance of Small- and Medium-Sized Enterprises: Evidence from a Randomized Natural Experiment in the UK Service Sector. *British Journal of Industrial Relations*, *54*(2), 409–421. https://doi.org/10.1111/BJIR.12094

Gnehm, A.-S. (2018). Text Zoning for Job Advertisements with Bidirectional LSTMs. In *Proceedings of the 3rd Swiss Text Analytics Conference - SwissText 2018, CEUR Workshop Proceedings* (Vol. 2226, pp. 66–74).

Goetze, W., & Aksu, B. (2018). Anforderungsprofile: Die Methode. Retrieved from http://www.anforderungsprofile.ch/index.cfm?action=act_getfile&doc_id=100052&

Görlitz, K., & Tamm, M. (2016a). The returns to voucher-financed training on wages, employment and job tasks. *Economics of Education Review*, *52*, 51–62.

Görlitz, K., & Tamm, M. (2016b). Revisiting the complementarity between education and training – the role of job tasks and firm effects. *Education Economics*, *24*(3), 261–279. https://doi.org/10.1080/09645292.2015.1006182

Grip, A. de, & van Loo, J. (2002). *The economics of skills obsolescence: a review*. Elsevier Science.

Jacobson, L., Lalonde, R. J., & Sullivan, D. (2005). The Impact of Community College Retraining on Older Displaced Workers: Should We Teach Old Dogs New Tricks? *ILR Review*, *58*(3), 398–415. https://doi.org/10.1177/001979390505800305

Konings, J., & Vanormelingen, S. (2014). The Impact of Training on Productivity and Wages: Firm-Level Evidence. *The Review of Economics and Statistics*, *97*(2), 485–497. https://doi.org/10.1162/REST_a_00460

Kredler, M. (2014). Experience vs. obsolescence: A vintage-human-capital model. *Journal of Economic Theory*, *150*, 709–739.

Leuven, E., & Oosterbeek, H. (2008). An alternative approach to estimate the wage returns to private-sector training. *Journal of Applied Econometrics*, *23*(4), 423–434. https://doi.org/10.1002/JAE.1005

Lovász, A., & Rigó, M. (2013). Vintage effects, aging and productivity. *Labour Economics*, *22*, 47–60. https://doi.org/10.1016/j.labeco.2012.08.005

MacDonald, G., & Weisbach, M. S. (2004). The economics of has-beens. *Journal of Political Economy*, *112*(S1), 289-310.

Mohr, S., Troltsch, K., & Gerhards, C. (2016). Job tasks and the participation of low-skilled employees in employer-provided continuing training in Germany. *Journal of Education and Work*, *29*(5), 562–583. https://doi.org/10.1080/13639080.2015.1024640

Neuman, S., & Weiss, A. (1995). On the effects of schooling vintage on experience-earnings profiles: Theory and evidence. *European Economic Review*, *39*(5), 943–955. https://doi.org/10.1016/0014-2921(94)00019-V

OECD (2005a). *Promoting Adult Learning*. Retrieved from https://www.oecd-ilibrary.org/content/publication/9789264010932-en https://doi.org/10.1787/9789264010932-en

OECD (2005b). *The Role of National Qualifications Systems in Promoting Lifelong Learning - An OECD Activity*. Retrieved from https://www.oecd.org/education/innovation-education/34376318.pdf

OECD (2006). Live longer, work longer. In *Ageing and Employment Policies*. OECD publishing Paris.

OECD (2019). *Fiscal challenges and inclusive growth in ageing societies* (2019 No. 27). OECD Economic Policy Papers.

Rosen, S. (1975). Measuring the obsolescence of knowledge. In *Education, income, and human behavior* (pp. 199–232). NBER.

Ruhose, J., Thomsen, S. L., & Weilage, I. (2019). The benefits of adult learning: Work-related training, social capital, and earnings. *Economics of Education Review*, *72*, 166–186.

Salvisberg, A. (2010). *Soft Skills auf dem Arbeitsmarkt: Bedeutung und Wandel*. Seismo Zürich.

Schwerdt, G., Messer, D., Woessmann, L., & Wolter, S. C. (2012). The impact of an adult education voucher program: Evidence from a randomized field experiment. *Journal of Public Economics*, *96*(7-8), 569–583.

State Secretariat for Economic Affairs (2021). Arbeitslosenstatistik. Retrieved from https://www.amstat.ch/MicroStrategy/servlet/mstrWeb?&evt=2001&src=mstrWeb.2001&folderID=FCF04E774B103632526774A54C47ACF3&hiddenSections=header,path,dockLeft,error,dockRight,dockBottom,footer&

Swiss Federal Statistical Office (2019). *Swiss Microcensus of Continuing Education ("Mikrozensus Aus- und Weiterbildung")*. Bundesamt für Statistik BFS.

Tamm, M. (2018). Training and changes in job Tasks. *Economics of Education Review, 67*, 137–147. https://doi.org/10.1016/j.econedurev.2018.09.007

Van Imhoff, E. (1989). Age structure, education, and the transmission of technical change. *Journal of Population Economics*, *1*(3), 167–181.

Violante, G. L. (2002). Technological Acceleration, Skill Transferability, and the Rise in Residual Inequality. *The Quarterly Journal of Economics*, *117*(1), 297–338. https://doi.org/10.1162/003355302753399517

Walker, J. (2009). The inclusion and construction of the worthy citizen through lifelong learning: a focus on the OECD. *Journal of Education Policy*, *24*(3), 335–351. https://doi.org/10.1080/02680930802669276

Tables & Figures:

Table 1— Training Participation and Training Characteristics

	N	*mean*	*SD*	*min*	*max*
Panel A. Lifelong Learning					
Training Participation: General	9,936	0.71	0.45	0	1
Training Participation: Work Reasons	9,936	0.60	0.49	0	1
Training Participation: Employer Sponsored	9,936	0.57	0.5	0	1
Number of Training Measures	9,936	1.86	2.00	0	20
Total Expenditures (worker) (in CHF)	4,525	531	1,558	0	25,100
Panel B. Training Measures					
Hard-Skill Training	9,936	0.38	0.49	0	1
Soft-Skill Training	9,936	0.30	0.46	0	1
Training Duration (in hours)	3,339	25.05	30.33	0	309
Average Costs per Course (worker) (in CHF)	3,339	205.69	525.40	0.00	8,367

Note: Authors' calculations with data from the SMCE. *Total Expenditures*, *Training Duration*, and *Average Costs per Course* are only available for the 2016 SMCE wave and explain the difference in the number of observations.

Table 2—Summary Statistics of Individual Characteristics, Formal Educational Backgrounds and Labor Market Outcomes

	N	*mean*	*SD*	*min*	*max*
Panel A. Labor Market Outcomes					
Employment	9,936	0.97	0.17	0	1
Wage (cond. employment)	9,649	95,360	58,552	6500	648,960
Panel B. Personal Characteristics					
Age	9,936	45.70	9.35	30	64
Male	9,936	0.53	0.50	0	1
Swiss	9,936	0.68	0.46	0	1
Married	9,936	0.60	0.49	0	1
Panel C. Formal Educational Background (Highest Diploma/Degree)					
No Compulsory Schooling	9,936	0.01	0.10	0	1
Compulsory Schooling	9,936	0.12	0.33	0	1
Vocational Education and Training Diploma	9,936	0.42	0.49	0	1
Baccalaureate	9,936	0.04	0.19	0	1
Tertiary Education Degree	9,936	0.40	0.49	0	1

Note: Authors' calculations with data from the SMCE.

Table 3—Labor Market Returns and Training Participation

Dependent variable	Employment	Wages
	(1)	(2)
HS_Spectrum (std.)	-0.0132***	0.1130***
	(0.004)	(0.011)
Train	0.0151***	0.1142***
	(0.006)	(0.014)
Train x HS_Spectrum (std.)	0.0137***	-0.0234*
	(0.005)	(0.012)
Constant	0.8205***	10.0645***
	(0.059)	(0.147)
Formal Education	YES	YES
Indiv. Characteristics	YES	YES
Observations	9,936	9,649
R-squared	0.020	0.226

Notes: *HS_Spectrum* refers to the location of the occupation on the hard-soft skill spectrum. *Cont_Educ* denotes the individual training participation (all training content). *Formal Education* is a set of dummy variables for the formal educational background. *Indiv. characteristics* include age (and its squared term), and dummies for male, Swiss native, single and the wave of the SMCE. Robust standard errors. Significance levels: * p<0.10, ** p<0.05, *** p<0.01.

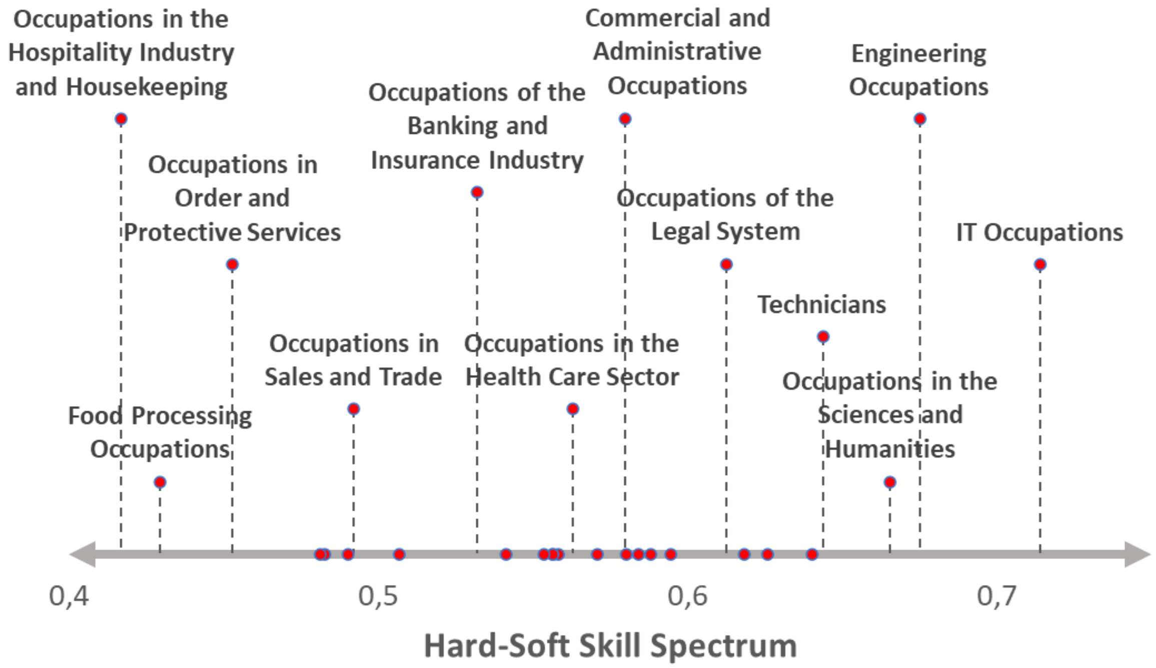

Figure 1. Location on the Hard-Soft Skill Spectrum for Selected Occupations
(*Notes:* Occupations at the 2-digit occupational level of the Swiss Standardized Classification of Occupations and pooled across SMCE survey waves. The hard-soft skill spectrum captures the relative importance of hard and soft skills at the occupational level. An occupation's location on the spectrum is determined by the percentage of words describing hard skills in the sum of all words describing hard and soft skills. For example, IT occupations are located at 0.71, which implies that 71% of the mentioned skills are hard skills and shows that IT occupations are very hard-skill intensive. To improve the readability of the figure, we display labels only for selected occupations, which serve as illustrative examples. The remaining occupations are marked as unlabeled dots.)

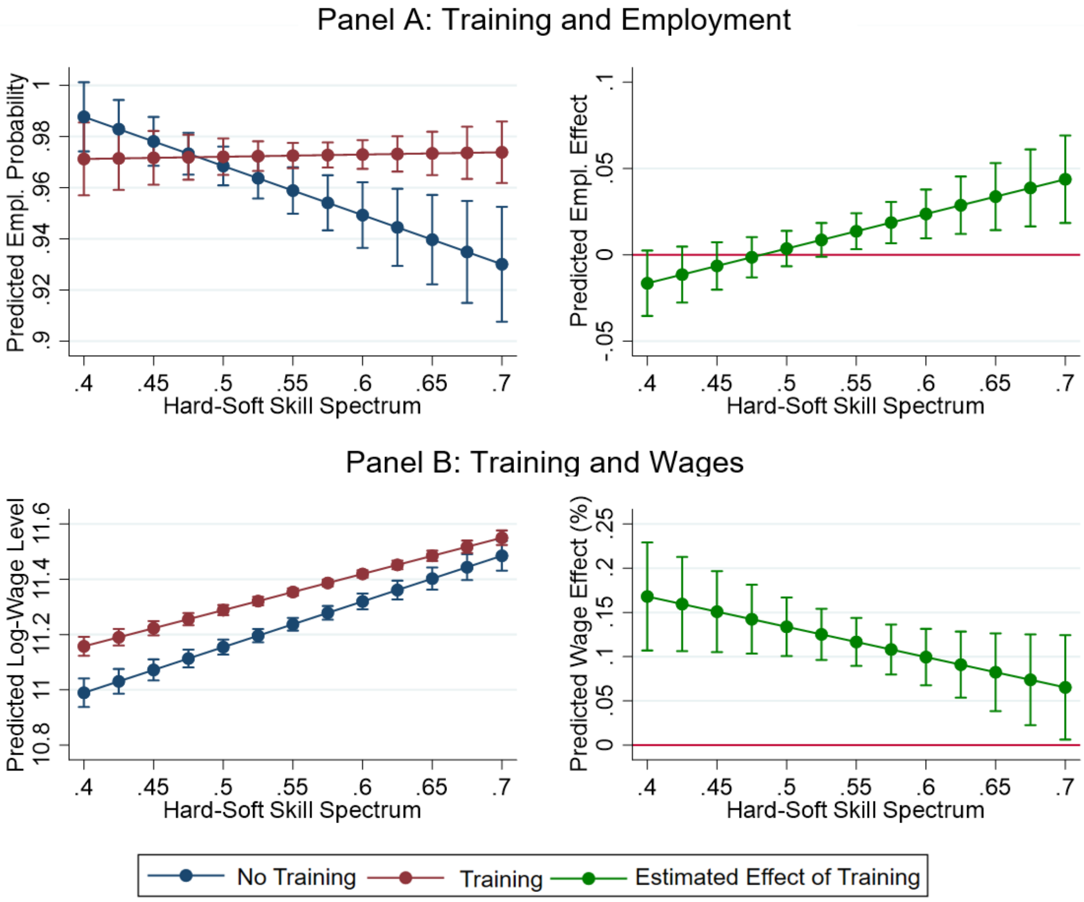

Figure 2. Marginal Effects of Training Participation at Different Location Along the Hard-Soft Skill Spectrum

(*Notes:* The graphs show predicted wage and employment levels, depending on training participation, and marginal effects from training participation, with 90 percent confidence intervals. Predicted levels and marginal effects are based on linear regression results from our main specification.)

Appendix:

Table A1—Occupations' Location on the Hard-Soft Skill Spectrum

Occupation	Location
IT Occupations	0.714
Engineering Occupations	0.675
Occupations in the Sciences and Humanities	0.666
Technicians	0.644
Technicians (all other)	0.640
Media Workers and Related Occupations	0.626
Technical Drawing Occupations	0.618
Occupations of the Legal System	0.613
Entrepreneurs, Directors, and Senior officials	0.594
Occupations in Advertising and Marketing, Tourism, and Trust Services	0.588
Metalworking and Mechanical Engineering Occupations	0.584
Occupations in Teaching and Education	0.580
Commercial and Administrative Occupations	0.580
Occupations in Chemical and Plastic Processing	0.571
Occupations in the Health Care Sector	0.563
Art Occupations	0.558
Occupations in Electrical Engineering, Electronics, Watchmaking, and Vehicle/Equipment Manufacturing	0.556
Machinists	0.556
Occupations in Construction	0.554
Other Production and Processing Occupations	0.541
Occupations of the Banking and Insurance Industry	0.532
Woodworkers and Paper Production and Processing Occupations	0.507
Occupations in Sales and Trade	0.492
Cleaning and Hygiene Occupations	0.490
Transport and Material Moving Occupations	0.483
Occupations in Care, Education, and Pastoral Care	0.481
Occupations in Order and Protective Services	0.453
Food Processing Occupations	0.429
Occupations in the Hospitality Industry and Housekeeping	0.417

Notes: Occupations at the 2-digit occupational level of the Swiss Standardized Classification of Occupations and pooled across SMCE survey waves.

Table A2—Labor Market Returns and Training Participation (3-Digit Level of the Swiss Standardized Classification of Occupations)

Dependent Variable	Employment	Wages
	(1)	(2)
HS_Spectrum (std.)	-0.0182***	0.1119***
	(0.006)	(0.015)
Train	0.0148***	0.1208***
	(0.005)	(0.014)
Train x HS_Spectrum (std.)	0.0176***	-0.0504***
	(0.006)	(0.016)
Constant	0.8309***	10.0574***
	(0.059)	(0.149)
Formal Education	YES	YES
Indiv. Characteristics	YES	YES
Observations	9,890	9,605
R-squared	0.021	0.216

Notes: *HS_Spectrum* refers to the location of the occupation on the hard-soft skill spectrum at the 3-digit level of the Swiss Standardized Classification of Occupations. *Cont_Educ* denotes the individual training participation (all training content). *Formal Education* is a set of dummy variables for the formal educational background. *Indiv. characteristics* include age (and its squared term), and dummies for male, Swiss native, single and the wave of the SMCE. Significance levels: * p<0.10, ** p<0.05, *** p<0.01.

Table A3—Labor Market Returns of Training (Narrowly Defined), Age 30-47

Dependent variable	Employment	Wages
	(1)	(2)
HS_Spectrum (std.)	-0.007	0.124***
	(0.004)	(0.012)
Types of Training		
▪ *Hard_Train*	0.019***	0.123***
	(0.007)	(0.019)
▪ *Soft_Train*	-0.022*	0.074***
	(0.011)	(0.021)
▪ *Soft_Train x Hard_Train*	0.002	-0.018
	(0.015)	(0.034)
▪ *Mixed_Train*	0.016**	0.026
	(0.008)	(0.017)
Occupational Skills as Moderator		
▪ ***Hard_Train x HS_Spectrum (std.)***	**0.009**	**-0.068*****
	(0.006)	**(0.018)**
▪ ***Soft_Train x HS_Spectrum (std.)***	**0.004**	**-0.044****
	(0.014)	**(0.020)**
▪ ***Hard_Train x Soft_Train x HS_Spectrum (std.)***	**-0.015**	**0.057***
	(0.016)	**(0.030)**
Constant	0.882***	9.220***
	(0.192)	(0.467)
Formal Education	YES	YES
Indiv. Characteristics	YES	YES
Observations	5,401	5,220
R-squared	0.023	0.237

Notes: *HS_Spectrum* refers to the location of the occupation on the hard-soft skill spectrum. *Hard_Train* and *Soft_Train* denote training with hard-skill and soft-skill skills, respectively. Following our narrow definition of hard and soft skills we assigned training measures in informatics, finance, production, and science to hard-skill training, whereas we assigned training measures in management, personality, and language to soft-skill training. *Mixed_Train* denotes training in mixed subjects (i.e., health and teaching). *Formal Education* is a set of dummy variables for the highest formal educational background. *Indiv. characteristics* include age (and its squared term), and dummies for male, Swiss native, single and the wave of the SMCE. Significance levels: * p<0.10, ** p<0.05, *** p<0.01.

Table A4—Labor Market Returns of Training (Narrowly Defined), Age 48-64

Dependent variable	Employment	Wages
	(1)	(2)
HS_Spectrum (std.)	-0.014***	0.098***
	(0.004)	(0.013)
Types of Training		
▪ *Hard_Train*	0.008	0.134***
	(0.008)	(0.021)
▪ *Soft_Train*	-0.000	0.125***
	(0.009)	(0.027)
▪ *Soft_Train x Hard_Train*	0.002	-0.074**
	(0.013)	(0.037)
▪ *Mixed_Train*	0.025***	0.041*
	(0.005)	(0.022)
Occupational Skills as Moderator		
▪ ***Hard_Train x HS_Spectrum (std.)***	**0.025***	**-0.049**
	(0.008)	**(0.021)**
▪ ***Soft_Train x HS_Spectrum (std.)***	**0.018**	**-0.006**
	(0.008)	**(0.023)**
▪ ***Hard_Train x Soft_Train x HS_Spectrum (std.)***	**-0.025**	**0.063***
	(0.016)	**(0.036)**
Constant	0.975***	11.923***
	(0.377)	(1.366)
Formal Education	YES	YES
Indiv. Characteristics	YES	YES
Observations	4,535	4,429
R-squared	0.030	0.230

Notes: *HS_Spectrum* refers to the location of the occupation on the hard-soft skill spectrum. *Hard_Train* and *Soft_Train* denote training with hard-skill and soft-skill skills, respectively. Following our narrow definition of hard and soft skills, we assigned training measures in informatics, finance, production, and science to hard-skill training, whereas we assigned training measures in management, personality, and language to soft-skill training. *Mixed_Train* denotes training in mixed subjects (i.e., health and teaching). *Formal Education* is a set of dummy variables for the highest formal educational background. *Indiv. characteristics* include age (and its squared term), and dummies for male, Swiss native, single and the wave of the SMCE. Significance levels: * p<0.10, ** p<0.05, *** p<0.01.

Table A5—Labor Market Returns and Training Types (Widely Defined), Age 30-47

Dependent variable	Employment	Wages
	(1)	(2)
HS_Spectrum (std.)	-0.008**	0.128***
	(0.004)	(0.013)
Types of Training		
▪ *Hard_Train*	0.018**	0.114***
	(0.007)	(0.019)
▪ *Soft_Train*	-0.030**	0.080***
	(0.014)	(0.025)
▪ *Soft_Train x Hard_Train*	0.017	-0.017
	(0.017)	(0.033)
Occupational Skills as Moderator		
▪ ***Hard_Train x HS_Spectrum (std.)***	**0.011***	**-0.060*****
	(0.006)	**(0.017)**
▪ ***Soft_Train x HS_Spectrum (std.)***	**0.003**	**-0.034**
	(0.016)	**(0.023)**
▪ ***Hard_Train x Soft_Train x HS_Spectrum (std.)***	**-0.015**	**0.032**
	(0.018)	**(0.030)**
Constant	0.879***	9.208***
	(0.193)	(0.468)
Formal Education	YES	YES
Indiv. Characteristics	YES	YES
Observations	5,401	5,220
R-squared	0.023	0.237

Notes: *HS_Spectrum* refers to the location of the occupation on the hard-soft skill spectrum. *Hard_Train* and *Soft_Train* denote training with hard-skill and soft-skill skills (widely defined). Following our wider definition of hard and soft skills, we assigned training measures in informatics, finance, production, and science to hard-skill training, while also including training measures in health and teaching (previously assigned to mixed training with the narrow definition). We assigned training measures in management, personality, and language to soft-skill training. *Formal Education* is a set of dummy variables for the highest formal educational background. *Indiv. characteristics* include age (and its squared term), and dummies for male, Swiss native, single and the wave of the SMCE. Significance levels: * p<0.10, ** p<0.05, *** p<0.01.

Table A6—Labor Market Returns and Training Types (Widely Defined), Age 48-64

Dependent variable	Employment	Wages
	(1)	(2)
HS_Spectrum (std.)	-0.016***	0.084***
	(0.005)	(0.014)
Types of Training		
▪ *Hard_Train*	0.021***	0.135***
	(0.007)	(0.021)
▪ *Soft_Train*	-0.002	0.137***
	(0.013)	(0.032)
▪ *Soft_Train x Hard_Train*	0.004	-0.064
	(0.014)	(0.039)
Occupational Skills as Moderator		
▪ ***Hard_Train x HS_Spectrum (std.)***	**0.024*** **	**-0.003**
	(0.007)	**(0.021)**
▪ ***Soft_Train x HS_Spectrum (std.)***	**0.022** **	**0.016**
	(0.010)	**(0.026)**
▪ ***Hard_Train x Soft_Train x HS_Spectrum (std.)***	**-0.028***	**-0.001**
	(0.015)	**(0.036)**
Constant	0.965**	11.958***
	(0.375)	(1.366)
Formal Education	YES	YES
Indiv. Characteristics	YES	YES
Observations	4,535	4,429
R-squared	0.029	0.229

Notes: *HS_Spectrum* refers to the location of the occupation on the hard-soft skill spectrum. *Hard_Train* and *Soft_Train* denote training with hard-skill and soft-skill skills (widely defined). Following our wider definition of hard and soft skills, we assigned training measures in informatics, finance, production, and science to hard-skill training, while also including training measures in health and teaching (previously assigned to mixed training with the narrow definition). We assigned training measures in management, personality, and language to soft-skill training. *Formal Education* is a set of dummy variables for the highest formal educational background. *Indiv. characteristics* include age (and its squared term), and dummies for male, Swiss native, single and the wave of the SMCE. Significance levels: * p<0.10, ** p<0.05, *** p<0.01.

Table A7—Correlations with the Hard-Soft Skill Spectrum

	Correlation between *HS_Spectrum* and Motivations/Benefits (r)
Motivation: Technological Change	0.0698***
Motivation: Switch Job	0.0098
Benefit: Promotion	-0.0230*

Note: Authors' calculations with data from the SMCE. Correlation coefficients (r) for motivations/benefits of training participation with the occupations' location on the hard-soft skill spectrum (*HS_Spectrum)*. Significance levels: * p<0.10, ** p<0.05, *** p<0.01.

Table A8—Labor Market Returns and Training Placebo

Dependent variable	Employment	Wages
	(1)	(2)
HS_Spectrum (std.)	-0.004	0.102***
	(0.003)	(0.006)
Train	0.014***	0.016
	(0.005)	(0.015)
Train x HS_Spectrum (std.)	**0.004**	**-0.004**
	(0.005)	**(0.014)**
Constant	0.828***	10.098***
	(0.059)	(0.147)
Formal Education	YES	YES
Indiv. Characteristics	YES	YES
Observations	9,936	9,649
R-squared	0.019	0.216

Notes: *HS_Spectrum* refers to the location of the occupation on the soft-hard skill-spectrum. *Train_Placebo* denotes training participation in lifelong learning measures in art, sports and household. *Formal Education* is a set of dummy variables for the highest formal educational background. *Indiv. characteristics* include age (and its squared term), and dummies for male, Swiss native, single and the wave of the SMCE wave. Significance levels: * p<0.10, ** p<0.05, *** p<0.01.

Table A9—Labor Market Returns and Training Participation
(Restricted Comparison Group)

Dependent variable	Employment	Wages
	(1)	(2)
HS_Spectrum (std.)	-0.016**	0.099***
	(0.01)	(0.02)
Train	0.033***	0.156***
	(0.01)	(0.02)
Train x HS_Spectrum (std.)	**0.016****	**-0.010**
	(0.01)	**(0.02)**
Constant	0.850***	10.036***
	(0.07)	(0.16)
Formal Education	YES	YES
Indiv. Characteristics	YES	YES
Observations	7,965	7,736
R-squared	0.022	0.228

Notes: We follow Leuven and Oosterbeek's (2008) comparison-group method and restrict the comparison group (i.e., no training participation) to individuals willing to participate in training but being hindered by internal and external circumstances. Nonparticipants without training aspirations are thus excluded. *HS_Spectrum* refers to the location of the occupation on the soft-hard-skill spectrum. *Train* denotes the individual training participation. *Formal Education* is a set of dummy variables for the highest formal educational background. *Indiv. characteristics* include age (and its squared term), and dummies for male, Swiss native, single and the wave of the SMCE. Significance levels: * p<0.10, ** p<0.05, *** p<0.01.

Table A10—Labor Market Returns and Training Types (Narrowly Defined), Age 30-47 (Restricted Comparison Group)

Dependent variable	Employment	Wages
	(1)	(2)
HS_Spectrum (std.)	-0.009	0.116***
	(0.006)	(0.015)
Types of Training		
▪ *Hard_Train*	0.026***	0.134***
	(0.008)	(0.021)
▪ *Soft_Train*	-0.014	0.086***
	(0.012)	(0.023)
▪ *Soft_Train x Hard_Train*	-0.006	-0.030
	(0.016)	(0.035)
▪ *Mixed_Train*	0.018**	0.032*
	(0.008)	(0.018)
Occupational Skills as Moderator		
▪ ***Hard_Train x HS_Spectrum (std.)***	**0.011**	**-0.061*****
	(0.007)	**(0.020)**
▪ ***Soft_Train x HS_Spectrum (std.)***	**0.006**	**-0.038***
	(0.015)	**(0.022)**
▪ ***Hard_Train x Soft_Train x HS_Spectrum (std.)***	**-0.017**	**0.051**
	(0.017)	**(0.032)**
Constant	0.864***	8.977***
	(0.211)	(0.519)
Formal Education	YES	YES
Indiv. Characteristics	YES	YES
Observations	4,484	4,330
R-squared	0.024	0.232

Notes: We follow Leuven and Oosterbeek's (2008) comparison-group method and restrict the comparison group (i.e., no training participation) to individuals willing to participate in training but being hindered by circumstances. Nonparticipants without training aspirations are thus excluded. *HS_Spectrum* refers to the location of the occupation on the hard-soft skill spectrum. *Hard_Train* and *Soft_Train* denote training with hard-skill and soft-skill skills, respectively. Following our narrow definition of hard and soft skills, we assigned training measures in informatics, finance, production, and science to hard-skill training, whereas we assigned training measures in management, personality, and language to soft-skill training. *Mixed_Train* denotes training in mixed subjects (i.e., health and teaching). *Formal Education* is a set of dummy variables for the highest formal educational background. *Indiv. characteristics* include age (and its squared term), and dummies for male, Swiss native, single and the wave of the SMCE . Significance levels: * p<0.10, ** p<0.05, *** p<0.01.

Table A11—Labor Market Returns and Training Types (Narrowly Defined), Age 48 - 64 (Restricted Comparison Group)

Dependent variable	Employment	Wages
	(1)	(2)
HS_Spectrum (std.)	-0.006	0.098***
	(0.004)	(0.018)
Types of Training		
▪ *Hard_Train*	0.007	0.136***
	(0.008)	(0.023)
▪ *Soft_Train*	-0.001	0.129***
	(0.010)	(0.029)
▪ *Soft_Train x Hard_Train*	0.003	-0.079**
	(0.014)	(0.039)
▪ *Mixed_Train*	0.026***	0.046**
	(0.006)	(0.023)
Occupational Skills as Moderator		
▪ ***Hard_Train x HS_Spectrum (std.)***	**0.017****	**-0.050****
	(0.008)	**(0.024)**
▪ ***Soft_Train x HS_Spectrum (std.)***	**0.009**	**-0.009**
	(0.008)	**(0.026)**
▪ ***Hard_Train x Soft_Train x HS_Spectrum (std.)***	**-0.016**	**0.066***
	(0.016)	**(0.039)**
Constant	0.979**	12.977***
	(0.423)	(1.480)
Formal Education	YES	YES
Indiv. Characteristics	YES	YES
Observations	3,481	3,406
R-squared	0.030	0.240

Notes: We follow Leuven and Oosterbeek's (2008) comparison-group method and restrict the comparison group (i.e., no training participation) to individuals willing to participate in training but being hindered by circumstances. Nonparticipants without training aspirations are thus excluded. *HS_Spectrum* refers to the location of the occupation on the hard-soft skill spectrum. *Hard_Train* and *Soft_Train* denote training with hard-skill and soft-skill skills, respectively. Following our narrow definition of hard and soft skills, we assigned training measures in informatics, finance, production, and science to hard-skill training, whereas we assigned training measures in management, personality, and language to soft-skill training. *Mixed_Train* denotes training in mixed subjects (i.e., health and teaching). *Formal Education* is a set of dummy variables for the highest formal educational background. *Indiv. characteristics* include age (and its squared term), and dummies for male, Swiss native, single and the wave of the SMCE. Nonparticipants without training aspirations excluded. Significance levels: * p<0.10, ** p<0.05, *** p<0.01.