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Does ICT affect the demand for vocationally educated workers?

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Abstract

This paper examines the effect of information and communication technologies (ICT) on the demand for workers in Switzerland. We compare the hypotheses that an increase in ICT leads to upskilling or job polarization and investigate their implications for countries where vocational education and training (VET) is the most widespread education program at the upper secondary level. Using data from a large employer–employee survey, we create a novel measure of ICT based on the percentage of ICT workers within firms. This measure allows us to assess the impact of ICT on the educational composition of the workforce by exploiting variation over time. We find that ICT has an upskilling effect from 1996 to 2018: ICT decreases the demand for low-skilled workers while increasing the demand for high-skilled workers, especially those with a tertiary vocational education. These results strongly suggest that VET is a valid alternative to a strictly academic education, because workers with a tertiary VET degree are as good, or better, at adjusting to technological change as workers with a tertiary academic education.

Keywords: Labor demand, Skill-biased technical change, Job polarization, Information and communication technologies, Vocational education and training

JEL Classification: E24, J24, O33

1 Introduction

The expansion of information and communication technologies (ICT) is one of the most significant trends in industrialized countries. The disappearance of occupations and employment resulting from an increase in ICT-based technologies such as automation and robotics has become a hotly debated subject in the media and among policymakers. Researchers even try to predict which occupations will become obsolete and how large the displacement effect on employment will be (e.g., Frey & Osborne, 2017).

The debate over the influence of technological change on labor has long been dominated by the skill-biased technical change (SBTC) hypothesis, which posits that technological development favors highly skilled occupations (Katz & Murphy, 1992). SBTC, also known as upskilling, implies a shift in labor demand from low-skilled to high-skilled workers. Nonetheless, the implications of this hypothesis were partially contradicted by studies from the USA (Autor et al., 2006) and the UK (Goos & Manning, 2007), both of which showed that employment growth mainly occurred in low- and high-skilled occupations while decreasing in the middle of the distribution. Goos & Manning (2007) define this phenomenon—which Autor et al. (2003) had originally linked to the routinization of jobs—as job polarization.

Nonetheless, US studies may be biased, because they presuppose a certain educational system that does not necessarily apply to other countries. Indeed, despite a growing number of studies on labor market polarization and the routinization of jobs, evidence is scarce for the effect of technological change on labor demand in countries where most workers have a vocational education and training (VET) diploma or a professional education and

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training (PET) degree.[1] Furthermore, some researchers argue that VET graduates are theoretically at a disadvantage in adjusting to technological change (e.g., Krueger & Kumar, 2004; Hanushek et al., 2017). However, evidence of the effect of technological change on the demand for VET workers is relatively scarce, and the little research that exists—in case of Germany, for example—is contradictory (Rendall & Weiss, 2016; Roy & Consoli; 2018).

This study extends current knowledge of the impact of ICT on the demand for workers with different types of education, among others with VET. As for ICT, there are many ways to measure its diffusion and intensity. In our analysis we focuses on the labor component of ICT. Concretely, to capture the extent of ICT in a firm, we created a novel measure of ICT based on the percentage of ICT workers within firms. Focusing on the labor component of ICT offers multiple advantages, compared for instance to ICT capital, which covers a significantly smaller portion of firms' outlay for ICT and is more subject to measurement errors.

As for the composition of the labor force, we subdivide workers into six groups, according to their highest educational level. In addition to academic university graduates, high school graduates, and untrained workers, we consider workers with upper secondary VET, workers with tertiary PET degrees (Federal Diploma of Higher Education or Advanced Federal or Diploma of Higher Education), and workers who have graduated from a University of Applied Sciences (UAS) (bachelor-granting three-year colleges teaching and conducting applied research). Analyzing six education groups allows a fine-grained analysis of differences between types of education. Our analysis draws on data from 1996 to 2018 in the Swiss Earnings Structure Survey (SESS), a biannual survey of firms, which is the largest representative firm survey in Switzerland.

To assess the effect of ICT on labor demand,[2] we use quantitative regression analysis. We estimate equations that explain the percentage of employees with a particular education level by the extent of ICT in the firm. To account for firms' unobserved heterogeneity, we apply pseudo-panel methods in our estimations. We include time*region fixed effects, which allow us to capture changes in labor supply and control for firm size and workers' characteristics.

Our results suggest that ICT has an upskilling effect during the 1996–2018 period. Specifically, we find evidence that ICT increases the demand for high-skilled workers while decreasing the demand for low-skilled ones. Our results further suggest that the upskilling effect is larger for firms in the manufacturing sector than those in the service sector. For firm size, our estimates indicate a polarizing effect of ICT in large firms but an upskilling effect in small- and medium-sized ones.

A limitation of this study's data needs stating from the outset. Our analysis is based on two different proxies for ICT occupations: one for 1996–2010 and the other one for 2012 onward. This division is made because a shift in the information collected in the SESS precludes having a single ICT measure for all samples. Although we provide evidence for the similarity of these two measures, we cannot rule out the possibility that the different results we find for the two periods can partly be linked to these two different proxies.

The contribution of our paper is threefold. First, we create a novel measure of ICT based on the percentage of ICT workers within firms, a measure easily transferable to other countries or different datasets. Second, we provide new evidence of the effects of ICT on the labor market in Switzerland. While most of the literature focuses on the US labor market, we contribute to the debate about the effect of ICT in a European country. Third, by focusing on a fine-grained distinction among workers' educations, we also contribute to the literature on the adaptability of VET-educated workers to technological change (e.g., Hanushek et al., 2017). Our study shows that the expansion of ICT increases the demand not only for tertiary academic workers but also for workers with a PET degree and particularly those with a degree from a UAS. This finding suggests that both PET and UAS tertiary degrees constitute a valid alternative to academic university education. Distinguishing among these three types of highest education levels is particularly valuable for many European countries—including Austria, Denmark, Germany, and Switzerland—where the majority of workers enter the labor market with an upper secondary VET education (Hoeckel & Schwartz, 2010).

The remainder of this paper is structured as follows. The following section describes some of the key features of the Swiss education system, mainly focusing on the peculiarity of the Swiss VET and PET. Section 3 reviews the literature on the effect of technological change on labor market demand and presents our hypotheses. Section 4 explains the estimation strategy, and Sect. 5 describes the data. Section 6 presents the results of the analysis and deals with the issue of reverse causality by providing a robustness test of our main results. Section 7 investigates whether the results for the entire time period also hold for sub-periods. Section 8 concludes.

[1] We use the terms VET and PET for educational programs that prepare students for labor market entry in specific occupations or trades.

[2] For simplicity, we refer to this as the effect of ICT on labor demand, while what our estimations actually measure is an equilibrium outcome.

2 The Swiss education system

The Swiss education system has an academic and a vocational track, both at the upper secondary and at the tertiary level. At the upper secondary level, there are two main options. First, there is the possibility to enter further general education via a general baccalaureate school (equivalent to high school), which prepares youngsters for further studies at the tertiary level, usually at universities. The proportion opting for this pathway is relatively small, constituting approximately 20% of youngsters enrolled at the upper secondary level (SERI, 2018).

The second possibility at the upper secondary level, also the most common, is to embark on vocational education, typically through a dual-track VET, which combines practical training within a firm and general education in a vocational school. This pathway provides youngsters with a solid foundation in a given occupation. There are around 250 occupations to choose from. Most dual-track VETs last 3 or 4 years and ends with a nationally recognized VET diploma that gives access to tertiary-level professional education if combined with sufficient work experience. In the Swiss context, VET at the upper secondary level forms the basis for lifelong learning and opens up a wealth of job prospects (SERI, 2018).

Swiss tertiary-level education comprises professional education, Universities of Applied Sciences (UAS), and conventional universities. Professional education imparts the competences needed to handle challenging technical or managerial activities. Admission to professional education is normally open to holders of a VET diploma. There are around 400 federal examinations and 57 study programs at colleges of higher education in eight professional fields. The proportion of VET graduates who, after some years of work experience, decide to pursue professional qualifications has increased slightly over the last decade, to almost one-third (SERI, 2018).

The federal vocational baccalaureate can be acquired in parallel to a VET diploma or as a one-year course after completion of VET. The federal vocational baccalaureate improves permeability and entitles students to continue to a UAS, preparing them for professional activities through practical studies and applied research. Study programs are structured according to the Bachelor–Master system. In line with the European higher education framework, UAS are characterized by teaching-based orientation and applied research.

The general baccalaureate schools (high schools) serve mainly as student generators for conventional universities. Baccalaureate holders have the highest transition rates to higher education, with more than three-quarters enrolling with a conventional university within 2 years of obtaining their baccalaureate degree (Wolter et al. 2018). For this reason, it is hard to find individuals in the labor market with a high school diploma as the highest level of education obtained. Admission to a conventional university with a federal vocational baccalaureate is also possible although not frequent. This transition normally requires following a one-year preparatory course and passing the University Aptitude Test. Similarly, transitioning from a general baccalaureate school to a UAS is also possible. Such transitions generally require one year of work experience (Swissuniversities, 2015).

The Swiss education system is characterized by a high degree of permeability. It is relatively easy for learners to switch between the vocational/professional and general education pathways and pursue further education and training opportunities. Wolter et al. (2018) provides a detailed description of the Swiss education system, the transition possibilities, and graduates' labor market outcomes.

3 Literature review and hypotheses

Despite a growing body of literature on the effect of ICT on labor demand, the question of whether ICT decreases the demand for workers remains unanswered. By contrasting the concepts of job polarization and upskilling, this section reviews the literature on ICT's effect on the labor market, summarizes the international evidence, and links specific findings to the Swiss labor context.

3.1 From skill-biased technical change to job polarization

The debate over the influence of ICT on occupational structure has long been dominated by the assumption that technological change favors highly skilled occupations (e.g., Katz & Murphy, 1992; Hansen & Birkinshaw, 2007; Goos et al., 2009). This assumption, known as the SBTC hypothesis, suggests that new technologies lead to higher productivity, especially for highly educated workers, who possess the necessary skills to use them (see Acemoglu, 2002; Hornstein et al., 2005, for a theoretical foundation of skill-biased technological change). SBTC thus posits that ICT shifts labor demand from unskilled to skilled workers.

The empirical literature confirms this positive relationship between ICT and the demand for workers' skills across countries. Autor et al. (1998) show that the SBTC hypothesis, as measured by computerization, fits several salient changes in the distribution of earnings in the USA. Goldin & Katz (2009) empirically show that this framework successfully considered changes in the skill premium and the demand for skills in the USA throughout the twentieth century.

However, as Acemoglu (1999) points out, the SBTC hypothesis is partly contradicted by the empirical observation that the employment structure in the US has become polarized—that is, employment in low- and high-paid occupations has increased, while the percentage of medium-paid occupations has decreased. Acemoglu & Autor (2011) also show that the distribution of employment in the USA across occupations "twisted" over the period 1980–2007. They point out that employment grew nearly monotonically in occupational skills during the 1980s, with the percentage of occupations below the median skill level declining and the percentage of occupations above the median increasing. During the 1990s, while employment growth continued to increase in the higher part of the distribution, it also increased modestly at the bottom. In contrast, the percentage of occupations around the median skill level decreased. Acemoglu & Autor (2011) call this pattern "job polarization." They also point out during the 2000s, the US labor market became further polarized by showing substantial growth at the bottom part of the skills distribution, while showing negative growth and no growth, respectively, in the middle and top part of the skills distribution.

Linking job polarization to the diffusion of ICT, Autor et al. (2003) argue that this job polarization reflects the routinization of jobs—and that understanding the labor market consequences of technical change calls for distinguishing between skills and tasks. This distinction is crucial because workers with a given level of skills can perform different tasks. These tasks, in turn, are differently affected by ICT. In their classic work, Autor et al. (2003) distinguish both between routine and non-routine tasks and between cognitive and manual tasks, finding that ICT has a negative impact on workers performing routine manual and routine cognitive tasks. In contrast, they find that ICT positively affects workers conducting non-routine cognitive tasks but has no effect on workers performing non-routine manual tasks.

Following the groundbreaking work of Autor et al. (2003), many scholars have further developed the task-based perspective. David & Dorn (2013) show that the expansion of service employment explains almost all the increase at the bottom of the occupational distribution. Autor et al. (2015) highlight that the effect of ICT on the percentage of workers performing routine tasks in the US manufacturing sector has weakened since the 1980s but intensified in the service sector. These findings suggest that the effect of ICT on the labor market is shifting from automation in the manufacturing sector to computerization of information processing in the service sector.

The polarization pattern applies to the USA and many European countries, as shown by Goos et al. (2009), who analyze labor evolution in 16 European countries between 1993 and 2006. They show that the decline in the percentage of middle-wage occupations in all 16 countries was accompanied by an increase in the percentage of high-wage occupations (in 13 countries) and an increase in low-wage occupations (in 11 countries). Michaels et al. (2014) test whether industry–country pairs with faster growth in ICT experienced a relatively faster growth of tertiary-educated workers. Using data from the USA, Japan, and nine European countries for the period 1980–2004, they show that industries with faster ICT growth raise the relative demand for high-skilled workers while reducing it for middle-skilled workers. Their results are thus consistent with the notion of ICT-based polarization.

However, despite the attention given to labor market polarization, evidence from countries where most workers have a VET degree—including Austria, Germany, and Switzerland—is scarce. This lack of evidence is worrying, given the theoretical argument that VET graduates are at a disadvantage in adjusting to technological change (e.g., Krueger & Kumar, 2004; Hanushek et al., 2017). Moreover, few empirical studies consider the effect of technological change on VET, and the results are contradictory.

For example, recent analyses by Roy & Consoli (2018) and Rendall & Weiss (2016), investigating employment polarization in Germany within the framework of task-biased technical change, reach opposing conclusions. Roy & Consoli (2018) show that regions with a high percentage of VET experienced a decline in routine jobs, suggesting occupational upskilling. In contrast, Rendall & Weiss (2016) find that regions with high percentages of VET students have less computer adoption and less employment polarization. They argue that this relatively lower computer adoption arises because the firm-specific investment in VET prevents firms from adopting new technologies. These contradictory findings highlight the need for further investigations into the relationship between ICT and VET.

For Switzerland, the evidence is even sparser than for Germany. One of the few relevant studies was undertaken by Oesch & Rodriguez Menes (2011), who analyze the development of occupational structure in Switzerland according to changes in wage distribution from 1990 to 2008. They focus on changes in skills and task composition, and find for Switzerland a decrease in low-skilled non-routine manual occupations. In total, their results suggest that labor evolution in Switzerland shows an increasing pattern of polarization. However, they do not measure the direct effect of digitalization but consider it as a possible explanation. Bolli et al. (2015), in a similar manner, investigate the occupation-specific unemployment risk and show that the unemployment rate of high-paid and low-paid occupational groups has grown less than that of medium-paid occupational groups. This finding is more consistent with the polarization pattern of the labor market. However, once again, the effect of digitization is not measured directly.

In contrast, Balsmeier & Woerter (2019) offer evidence of the impact of digitization on job creation or destruction. Using a representative survey of Swiss firms, they measure investments in ICT capital at firm level. Their analyses suggest that increased investment in digitalization is associated with increased employment of high-skilled workers, while it reduces the employment of low-skilled workers. This finding is more in line with the upskilling hypothesis than with the polarizing one. The authors' analysis focuses on dividing workers into three major groups based on their education.

3.2 Hypotheses

We develop our research hypothesis from the theoretical framework and empirical evidence. As the literature is inconclusive regarding the effect of ICT on the proportion of workers with different levels of education, we formulate two opposing hypotheses.

First, if the SBTC hypothesis holds for Switzerland, ICT can be expected to have an upskilling effect across education levels. We thus hypothesize as follows:

H1a ICT has an upskilling effect, i.e., the effect of ICT on the demand for workers follows an increasing linear pattern, from untrained toward tertiary-level educated workers.

Second, if the job polarization hypothesis holds for Switzerland, a U-shape effect can be expected across the education levels. We thus formulate the following hypothesis:

H1b ICT has a polarizing effect, i.e., the effect of ICT on the demand for workers follows a U-shape across the education levels.

4 Empirical strategy

This section discusses the empirical strategy we use to assess the effect of ICT on the demand for workers. We begin by discussing how we operationalize ICT. We then present the pseudo-panel approach, which allows us to include firm fixed effects in a system of repeated cross sections. In this step, we provide detailed information on how we construct the cells and the necessary conditions, allowing us to obtain consistent estimates from repeated cross sections. We then briefly discuss the advantages that a generalized method of moments (GMM) can provide in solving potential problems of reverse causality inherent the fixed effects estimations.

4.1 Operationalizing ICT

Firms can engage in many types of ICT investments. According to Kaiser (2003), ICT could refer, among other things, to expenditure in physical ICT capital (hardware, telecommunications equipment), expenditure for ICT workers, and expenditure for ICT services bought externally (e.g., programming services). This considerable expenditure might reflect diverse technologies. Nevertheless, the economic theory of supermodularity developed by Milgrom & Roberts (1990; 1995), suggests that firms' ICT investment strategies are often combined, so that complementarities between firms' ICT investment strategies exist.

In this paper, we approximate ICT by considering only the labor component. Hence, we neglect the capital component of ICT. There are three reasons for approximating ICT based on ICT workers only. First, labor expenditure constitutes a significant portion of firms' outlay for ICT (Tambe & Hitt, 2012). Second, the literature has largely shown the complementary relation between ICT workers and ICT usage (Caroli & Van Reenen, 2001; Hempell, 2003; Arvanitis & Loukis, 2009; Hagsten & Sabadash, 2017). Third, it is much easier to measure the number of ICT workers than to measure the stock of ICT capital. Furthermore, as highlighted by Taştan & Göne (2020), there may be fewer concerns about ICT employment measurement errors than ICT capital measurement errors.

4.2 Pseudo-panel approach

To assess the effect of ICT on the demand for workers, we use a quantitative regression analysis. We estimate equations that relate the percentage of non-ICT workers with a particular educational level to the percentage of ICT workers in a firm. To avoid the mechanical effect that an increase in ICT workers has on workers' educational composition within a firm, we exclude ICT workers from the dependent variable. By so doing, we avoid being misled by a potential situation in which ICT workers are highly represented among a specific education group (e.g., among academic-educated workers), resulting in the employment effect being driven by education rather than ICT. As we do not account for the effect of ICT on ICT workers, our empirical strategy provides a lower bound of the effect of ICT on labor demand.[3]

Observing firms' percentages of ICT workers and their workforce composition over time allows us to apply firm fixed effects, thereby preventing possible bias due to time-invariant unobserved firm-specific heterogeneity.

[3] Estimations including ICT workers in the percentage of workers with a particular education level provide qualitatively similar results.

As the data used in this study consist of independent, repeated cross sections, the inclusion of firm fixed effects is not feasible. However, the pseudo-panel methods, which consider stable groups of firms with similar characteristics (e.g., geographical location, industry, firm size), rather than single firms over time, constitute a valid alternative (Deaton, 1985). In the pseudo-panel method, firm variables are replaced by their intra-group means. The necessary condition is that cells (i.e., groups of firms) are fixed over time. If this condition holds, firm fixed effects can be replaced by cell fixed effects, and the model can be estimated as a standard panel fixed effect.

To illustrate the pseudo-panel method, we start by presenting a standard panel fixed effect. Assume that we have genuine panel data that allow us to follow firms over time. We can estimate the effect of ICT on the percentage of employees with a particular education level in a firm as follows:

$$y^l_{it} = \alpha_i + \beta_1 ICT_{it} + \beta_2 X_{it} + \gamma_{rt} + \epsilon_{it} \tag{1}$$

where y^l_{it} is the percentage of employees with education level l in firm i at time t, who are not classified as ICT workers. ICT_{it} is the percentage of ICT occupations in firm i at time t, and X_{ti} is a vector of control variables. γ_{rt} is a dummy for combinations of region and year, capturing time-region-specific trends. ϵ_{it} is the error term, which is clustered at the firm level. In genuine panel data, α_i is a fixed unknown parameter.

For repeated cross sections, Deaton (1985) suggests the use of cells for obtaining a consistent estimate of β with repeated cross sections. Cells c are groups of firms sharing certain common characteristics. Firms belong to one cell, which remains fixed for all periods. If cells are based on a large number of individual observations, we can assume that cell averages over time are fixed ($\bar{\alpha}_{ct} = \alpha_c$), so that a natural estimator of β yields a fixed effect estimator (sometimes called "within estimator") on the pseudo-panel. Aggregating observations at the cell level, we can thus rewrite the equation as follows:

$$\bar{y}^l_{ct} = \alpha_c + \beta_1 \overline{ICT}_{ct} + \beta_2 \bar{X}_{ct} + \gamma_{rt} + \bar{u}_{ct} \quad c = 1, \dots C \quad ; \quad t = 1, \dots, T \tag{2}$$

where $\bar{y}^l_{ct}$ is the percentage of employees with education level l in cell c at time t, $\overline{ICT}_{ct}$ ct is the percentage of ICT-intensive occupations in cell c at time t, and $\bar{X}_i$ is a vector of control variables averaged across cell c in time t. γ_{rt} still captures time-region-specific trends. $\bar{u}_{ct}$ is the error term, which now is clustered at the cell level.

The pseudo-panel approach has the additional benefit that the use of cell means averages out the measurement errors of individual firms (Antman & McKenzie, 2007). We construct cells c, grouping together firms with characteristics considered similar. According to Guillerm (2017), a good selection criterion must (a) be based on firm-level characteristics that do not change over time, (b) generate enough cells to reduce measurement errors, and (c) not generate not too many cells, to prevent loss of the necessary within-cell variability.

We construct pseudo-panel cells by grouping the firm-level observations by year, regions (106), firm size (three), and industry defined at the two-digit level (55 classes derived from NOGA 2002 classification for 1996–2010 and 41 classes derived from NOGA 2008 classification for 2012–2018). We thus potentially create 17,490 cells per year for 1996–2010 and 13,038 cells per year for 2012–2018.

Not all combinations of *industry * region * firm size* exist in the data, resulting in 48,386 cells over the period 1996–2018 with an average of about 61 firms per cell. We thus obtain an unbalanced quasi-panel comprising observations of each cell c at different times. We calculate the percentages of workers with education level l and the average of all explanatory variables for each cell.

As pointed out by Verbeek & Nijman (1992), cell averages should be based on approximately 100 observations to minimize possible sampling error. Because the way we construct the cells generates an average slightly below this threshold, we test alternative possibilities for grouping firms. We lower the level of detail in each of the three parameters we use to construct the cells. By considering only two firm sizes instead of three, we generate 45,807 cells with an average of approximately 65 firms per cell. By considering 16 supra-regional labor markets instead of 106 local labor market regions, we generate 14,181 cells with an average of approximately 234 firms per cell. Finally, by considering 18 branches of the economy instead of the 55 (41) industries defined at the two-digit level for the period 1996–2010 (2012–2018), we generate 26,367 cells with an average of approximately 160 firms per cell. All three variations in how we construct the cells lead to qualitatively similar results[4].

4.3 GMM approach

While the fixed effects estimation of Equation 2 accounts for possible time-invariant cell-specific effects, it does not control for potential reversed causality. In this case, reverse causality would occur if changes in the educational composition of the workforce would lead to higher demand for ICT workers. Furthermore, unobservable factors affecting workforce composition and ICT adoption could make the demand for labor endogenous. This potential problem has been documented by studies showing that workforce composition is a crucial factor in

[4] See Tables 15, 16, and 17 in the Appendix.

determining ICT adoption and usage (see, e.g., Bresnahan et al., 2002; Arvanitis, 2005; Falk & Biagi, 2017). To deal with potential problems of reverse causality in our fixed effects estimations, we use the system GMM estimator developed by Arellano & Bond (1991), which instruments variables by the corresponding lagged values and differences.

5 Data and description of variables

To estimate the effect of ICT on the demand for workers, we use the Swiss Earnings Structure Survey (SESS), a firm survey conducted by the Swiss Federal Statistical Office (SFSO) every 2 years since 1994. The SESS covers between 16.6% (1996) and 50% (2010) of total employment in Switzerland, thus constituting the largest representative firm survey in the country. Participation in the survey is mandatory.

The SESS is a repeated cross section of workers in Switzerland, reflecting the employment situation in October of the corresponding year. Every wave is a new stratified random sample of private and public firms with at least three full-time workers. Stratification covers firm size, two-digit industry affiliation, and geographic location. The sampling occurs at both the firm and employee levels. The SFSO selects firms from the Swiss Business and Enterprise Register. Firms then select the employees for whom they provide the information. Firms with fewer than 20 workers have to report information on all employees. Firms with between 20 and 50 workers can, if they wish, report information on every second employee. Firms with more than 50 workers can, if they wish, report information on every third employee. In the last two cases, firms are expected to select workers at random.

The SESS collects detailed information about workers' and firms' characteristics. We restrict the sample by including only individuals aged between 18 and 65 who work in the private sector, with full educational information. We focus on 1996–2018, as these waves contain all the information necessary for our empirical strategy. We study only private sector firms, because SESS coverage of the public sector is not complete for our time period.

At the firm level, we construct a measure of total employment based on the number of full-time equivalent (FTE) workers in the firm. We also use the number of FTEs to create a firm-size classification. We classify firms as small if they employ less than 50 FTE workers, medium if they employ between 50 and 249 FTE workers, and large if they employ more than 250 FTE workers. Industry affiliation is defined according to the NOGA 2002 classification (55 classes in total) for the waves before 2010 and the NOGA 2008 classification (41 classes in total) for the waves after 2012. The SESS reports firms' locations according to spatial mobility (MS) regions, which the SFSO defines as homogeneous micro-regions representing local labor markets (Schuler et al., 2005). MS-regions are thus appropriate for our analysis of the labor market effect of ICT on the demand for VET-educated workers.

At the worker level, the two key variables in our analysis are ICT and education. For education, we calculate for each firm the percentage of workers according to the highest level of education achieved. We create six educational groups. "Untrained" workers have no post-compulsory education or no officially recognized firm-internal vocational training.[5] "VET" workers have an upper secondary VET education (either dual-VET or full-time VET school). "High school" workers have an upper secondary academic education. This group is relatively small, as only a few workers enter the labor force with an academic upper secondary diploma as their highest level of education (i.e., most continue to tertiary academic education). "PET" workers have a tertiary vocational degree from a Professional Education and Training College or have passed a Federal or Advanced Federal Exam. "UAS" workers have a tertiary vocational degree from a University of Applied Sciences. "Academic" workers have a tertiary academic degree from an academic university.

Figure 1 presents the evolution of workers' education as a percentage of total employment. This graph shows that the percentage of VET workers is the largest in the workforce and has remained almost constant at around 50% from 1996 to 2018. In contrast, the percentage of Untrained workers declined over time. Nevertheless, in 2018 the group of Untrained workers was still the second largest, at roughly 20% of the workforce. While the remaining four groups are relatively small, each representing 10% or less of the workforce, all four show a stable or positive trend over time. Both PET and University workers almost doubled their percentage, from around 5% in 1996 to around 10% in 2018. UAS workers remain relatively constant throughout the period at around 5% of the workforce.[6] High school workers, although showing a significant increase over time, remain the smallest group.

To capture the extent of ICT in a firm, we use two proxies to cover the two periods, one based on ICT occupations and the other on ICT tasks. This is because a shift in the information collected in the SSES, which occurred

[5] To this group we add, for 1996–2010, all workers classified as "others." This classification was not continued in the waves starting in 2012.

[6] The small increase noticeable between 2016 and 2018 can partly be explained by a change in procedure by the SFSO, which as of 2018 retrospectively considers certificates from "Höheren Technischen Lehranstalten" (HTL) and "Höheren Wirtschafts- und Verwaltungsschulen" (HWV) as UAS-level degrees and no longer as PETs. Estimates that exclude the 2018 wave, and thus allow these degrees to always be ordered in the PET category, provide qualitatively similar results.

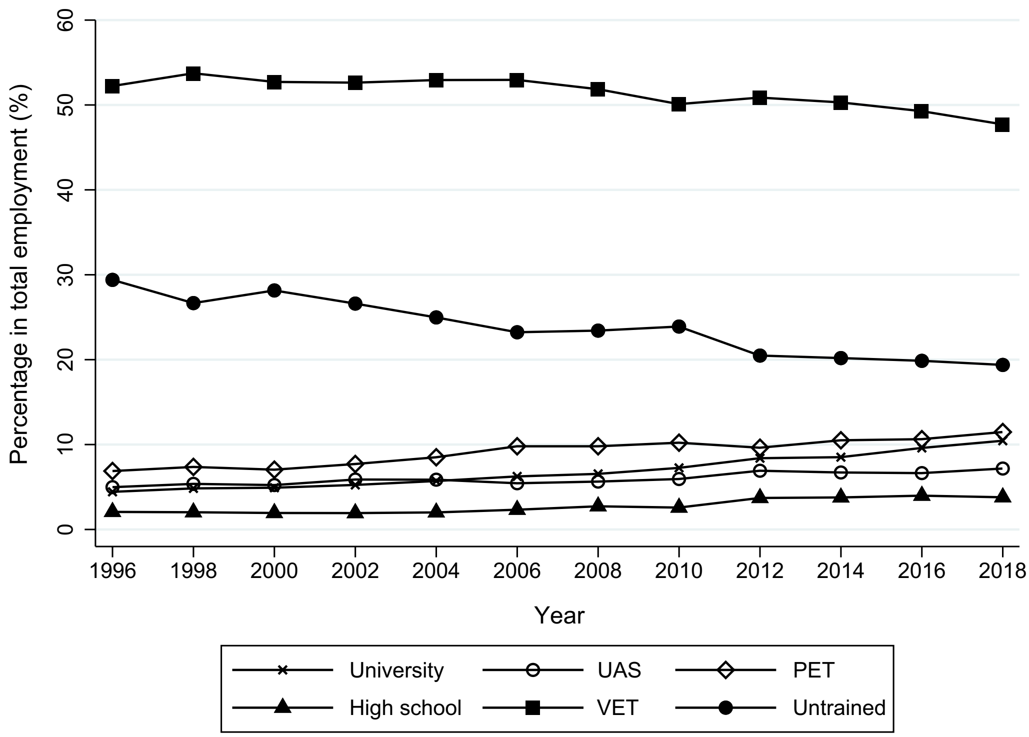

Fig. 1 Educational composition over time

between the 2010 and 2012 waves, precludes having a single ICT measure for all samples. The first measure of ICT, which applies to the period 2012–2018, is based on ILO (2012), which defines ICT occupations based on the ISCO-08 classifications. As Table 1 reports, ILO (2012) defines ICT workers as those working in ISCO-08 occupations "Information and Communication Technology Professionals" and "Information and Communication Technicians." As the SESS only covers ISCO in the waves after 2012, we use this proxy only for the second period.

As the SESS does not contain ISCO classifications before 2012, we use a different proxy for ICT for 1996–2010, based on a combination of tasks and requirement levels. Indeed, according to Cangemi et al. (2015), the main SESS criteria for classifying workers in the ISCO occupations after 2012 are the tasks and the requirement levels necessary for fulfilling a job. As tasks and the requirement levels are the antecedents of the occupation variable, we use them to construct a proxy for occupations in the 1996–2010 waves.

This proxy for ICT is based on two variables: tasks and requirement levels. The first variable captures the tasks carried out by workers, grouped by fields such as "setting up, operating, and maintaining machines." While these tasks resemble the "Generalized Work Activity" in the US O*NET Program, tasks in SESS are less detailed, differentiating only 24 activities as opposed to O*NET's

Table 1 ICT occupations according to ISCO-08 classification

Code	Title
25	Information and Communication Technology Professionals
251	Software and Applications Developers and Analysts
2511	Systems Analysts
2512	Software Developers
2513	Web and Multimedia Developers
2514	Applications Programmers
2519	Software and Application Developers and Analysts Not Elsewhere Classified
252	Database and Network Professionals
2521	Database Designers and Administrators
2522	Systems Administrators
2523	Computer Network Professionals
2529	Database and Network Professionals Not Elsewhere Classified
35	Information and Communication Technicians
351	Information and Communications Technology Operations and User Support Technicians
3511	Information and Communications Technology Operations Technicians
3512	Information and Communications Technology User Support Technicians
3513	Computer Network and Systems Technicians
3514	Web Technicians
352	Telecommunications and Broadcasting Technicians
3521	Broadcasting and Audiovisual Technicians
3522	Telecommunications Engineering Technicians

Source: ILO (2012)

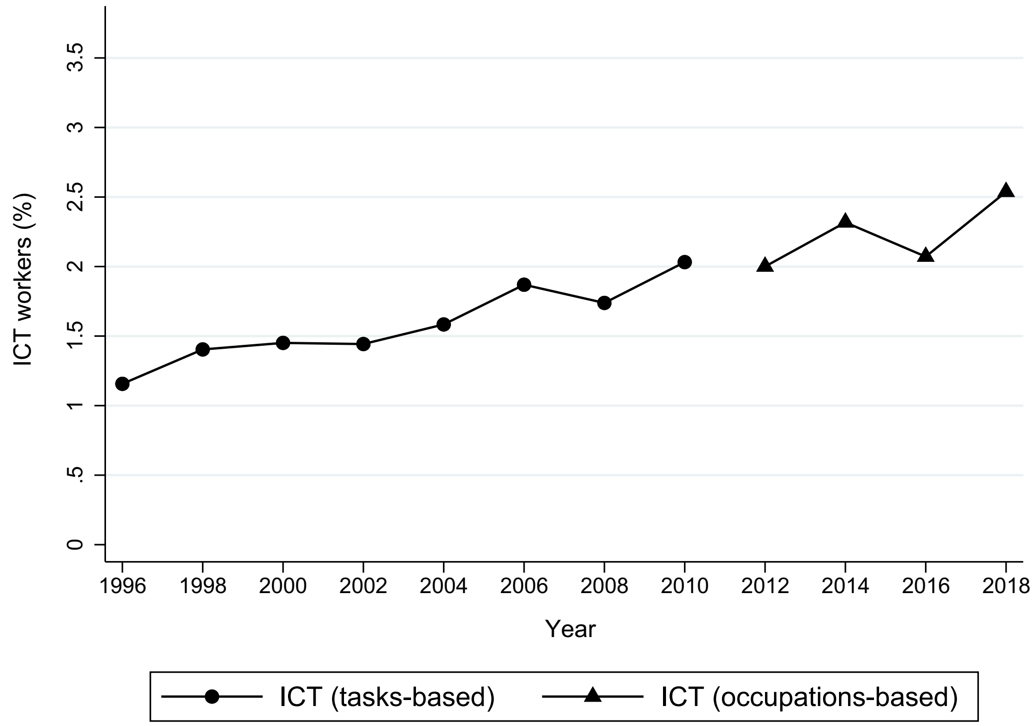

Fig. 2 Percentage of ICT workers according to the two proxies

41 (Tsacoumis & Willison 2010). In the SESS, each person is assigned to one task, and for our measure we only consider those performing the "Analyzing, Programming, Operation" task as ICT workers. The second variable we use in constructing the proxy for 1996–2010 is the requirement level. This variable uses four categories to measure how demanding and difficult the work is. We restrict this variable by considering only workers at requirement level 4 (denoting a job involving the most demanding and difficult work) or level 3 (a job requiring independent and qualified work).[7] As for those with level 2 (denoting a job requiring professional and technical skills) or level 1 (a job involving simple and repetitive activities), we do not consider them ICT workers.

Figure 2 reports the evolution of our two ICT proxies. It shows that the percentage of ICT workers, according to the task-based definition, measures from around 1% in 1996 to 2% in 2010. The percentage of ICT workers, according to the occupations-based measure, increases from around 2% in 2012 to 2.5% in 2018. Although theoretically these two variables are not completely comparable—the first describes ICT tasks, while the second refers to ICT occupations—this figure shows that our proxy for 1996–2010 is close to the percentage of ICT workers based on ICT occupations. Our procedure is further supported by Braun-Dubler et al. (2016), who also use the activities classified as "Analyzing, Programming, Operation"—based on the SESS dataset—to investigate the evolution of salaries in ICT occupations. For further worker-level information, we use age, gender, part-time, and tenure.[8]

We collapse the firm-level data of 11,575,341 workers and aggregate waves in a dataset of 243,123 and 128,011 observations for 1996–2010 and 2012–2018, respectively. Table 2 reports the firm-level summary statistics of the main variables used for the empirical analysis for the entire period and both sub-periods.

[7] According to the SESS codebook, in the waves from 2012, ISCO-08 occupations 20–26 have requirement level 4, while ISCO-08 occupations 30–35 have requirement level 3. According to the ILO (2012), ICT occupations correspond to ISCO-08 classes 25 and 35. Thus, we restrict our definition of ICT workers to those having requirement levels 3 and 4.

[8] SFSO imprecisely coded workers with less than one year of tenure with a missing value in the wave preceding 2004. Therefore, we cannot distinguish between workers with zero and missing values of tenure in 1996–2002. Excluding all observations with a missing value of tenure would reduce the sample size significantly, because the percentage of missing values in the tenure variable lies between 5% and 10% in the waves from 1996 to 2002 but is less than 0.4% from 2004. To avoid losing a considerable percentage of workers, we correct this variable by adopting a consistent (albeit imperfect) definition of tenure—by recoding all missing values to zero in all waves.

6 Estimation results

This section presents the results of our estimation procedure, identifying the effect of ICT on the proportion of workers grouped by their highest education level. We start by presenting the results for the pseudo-panel method. We then present the result for a generalized method of moments (GMM), which deals with potential problems of reverse causality of the fixed effects estimations.

6.1 OLS with fixed effect

Table 3 reports the results for 1996–2018. Columns (1) to (6) use the percentage of the six educational groups in this paper as a dependent variable: Untrained, VET, High school, PET, UAS and University. All estimations include time*MS-region fixed effects and control for total employment in the firm, firm averages of tenure and age, and the percentage of part-time and female workers.[9] The coefficients of interest are those in the first row of the table, which reports the effect of the percentage of ICT workers with a given education. It is noteworthy that the inclusion of time dummies allows us to account for the general trend of increasing percentage of workers with tertiary education that occurred during the considered period previously documented in Figure 1. The coefficients for ICT thus capture the additional "upskilling" effect experienced by firms, which increased their ICT employment.

The coefficient for *ICT* in column (6) is positive and statistically significant. The coefficient of 0.0797 means that a one percentage-point increase in ICT workers results in an average 0.08 percentage-point increase in university workers. Considering that the average percentage of ICT workers is 2% and that the average percentage of University workers is approximately 5.4%, this finding implies that an increase in the percentage of ICT workers from 2% to 3% is associated with an increase in University workers from 5.4% to approximately 5.5%.

The coefficient in column (5) suggests that the effect of *ICT* is larger for UAS workers. A test of pairwise equality suggests that the coefficient for UAS is statistically different from that of University. The coefficient of *ICT* in column (4), which is also positive and statistically significant, is smaller for PET workers than for University or UAS workers. The coefficient of *ICT* in column (3) is positive and statistically different from zero but smaller than the previous ones. This coefficient suggests a smaller effect of ICT growth on the percentage of workers with high school as the highest level of education. In contrast, the *ICT* coefficients in columns (2) and (1) indicate that for Untrained workers, and especially for VET workers, an increase in *ICT* reduces their employment.

The values for *ICT* suggest patterns more in line with the upskilling hypothesis (H1a) than the job polarization hypothesis (H1b). Indeed, we observe that ICT increases the demand for workers monotonically along

Table 2 Firm-level summary statistics

	N	Mean	SD	Min	Max
1996–2018					
Untrained	371134	0.20	0.29	0	1
VET	371134	0.52	0.35	0	1
High school	371134	0.03	0.11	0	1
PET	371134	0.11	0.19	0	1
UAS	371134	0.06	0.16	0	1
University	371134	0.08	0.19	0	1
ICT workers	371134	0.02	0.10	0	1
Total employment	371134	31.19	267.09	1	38740
Tenure	371134	6.94	4.93	0	68.5
Age	371134	40.66	6.95	18	64.0
Share of part-time workers	371134	0.38	0.35	0	1
Female	371134	0.45	0.33	0	1
1996–2010					
Untrained	243123	0.21	0.29	0	1
VET	243123	0.54	0.34	0	1
High school	243123	0.02	0.09	0	1
PET	243123	0.10	0.19	0	1
UAS	243123	0.06	0.15	0	1
University	243123	0.06	0.17	0	1
ICT workers (task-based)	243123	0.02	0.10	0	1
Total Employment	243123	28.44	219.49	1	38740
Tenure	243123	7.07	4.93	0	49
Age	243123	40.10	6.93	18	64
Share of part-time workers	243123	0.36	0.34	0	1
Female	243123	0.43	0.33	0	1
2012–2018					
Untrained	128011	0.18	0.28	0	1
VET	128011	0.49	0.35	0	1
High school	128011	0.05	0.13	0	1
PET	128011	0.11	0.20	0	1
UAS	128011	0.07	0.17	0	1
University	128011	0.10	0.22	0	1
ICT workers (occupation-based)	128011	0.02	0.10	0	1
Total employment	128011	36.41	339.53	1	37036
Tenure	128011	6.68	4.90	0	68.5
Age	128011	41.72	6.87	18	64
Share of part-time workers	128011	0.42	0.35	0	1
Female	128011	0.47	0.33	0	1

[9] These control variables are averaged over the values of all firms in a given cell. By so doing, we consider workers' average characteristics independently of the educational group. Robustness tests in which we include the educational groups' averages provide qualitatively similar results.

Table 3 Pseudo-panel FE estimation

	(1) Untrained	(2) VET	(3) High school	(4) PET	(5) UAS	(6) University
ICT	− 0.0983***	− 0.188***	0.0299**	0.0569**	0.120***	0.0797***
	(0.0252)	(0.0307)	(0.0126)	(0.0221)	(0.0178)	(0.0254)
Firm total employment	0.0000123***	− 0.0000108***	− 0.000000321	− 0.000000135	− 0.000000740	− 0.000000298
	(0.00000231)	(0.00000248)	(0.000000634)	(0.00000118)	(0.000000835)	(0.000000934)
Tenure	− 0.00552***	0.00758***	− 0.0000482	0.00172**	− 0.000859	− 0.00288***
	(0.00129)	(0.00151)	(0.000441)	(0.000785)	(0.00616)	(0.000682)
Tenure squared	0.0000956**	− 0.000167***	0.00000910	− 0.0000351	0.0000486***	0.0000485**
	(0.0000449)	(0.0000511)	(0.0000147)	(0.0000269)	(0.0000211)	(0.0000216)
Age	0.00698**	− 0.0292***	− 0.00417***	0.00648***	0.00669***	0.0132***
	(0.00285)	(0.00332)	(0.00108)	(0.00181)	(0.00136)	(0.00182)
Age squared	− 0.0000340	0.000310***	0.0000353***	− 0.0000773***	− 0.0000820***	− 0.000152***
	(0.0000349)	(0.0000407)	(0.0000128)	(0.0000224)	(0.0000170)	(0.0000231)
Part-time dummy	0.0378***	− 0.0386***	0.00848***	− 0.0247***	0.0204***	− 0.00341
	(0.0085)	(0.00880)	(0.00263)	(0.00437)	(0.00421)	(0.00458)
Male	0.0119	0.0455***	0.00872***	− 0.00734	− 0.0435***	− 0.0153***
	(0.00947)	(0.0108)	(0.00304)	(0.00523)	(0.00552)	(0.00546)
Time * MS-region FE	✓	✓	✓	✓	✓	✓
N	48386	48386	48386	48386	48386	48386
Mean dependent variable	0.223	0.553	0.0250	0.0919	0.0537	0.0539

The table shows OLS coefficients of fixed effects estimates of a firm pseudo-panel with cells defined based on MS-region, industry, and firm size. Standard errors in parentheses are clustered at the cell level. *N* reports the number of pseudo-panel cells that contain at least one firm. The main explanatory variable measures the cell percentage of ICT workers according to ICT tasks (1996-2010) or ICT occupations (2012-2018). Estimates further control for time*MS-region fixed effects and cell averages of total employment, tenure, age, part-time status, and gender. Each column shows the results for a different dependent variable measuring the percentage of workers with a particular education within the cell

$^{*}P < 0.10$, $^{**}P < 0.05$, $^{***}P < 0.01$

the education distribution. Specifically, we find support for our hypothesis that ICT decreases the demand for untrained workers while increasing the demand for PET, UAS, and University workers. The effect on the demand for middle-educated workers is more nuanced. On the one hand, ICT decreases the demand for upper secondary VET workers, although this decrease is less pronounced than that for Untrained workers. On the other hand, ICT has a small but positive effect on the demand for high school workers.

In Sect. 3.2, when formulating our hypotheses, we did not differentiate our expectations for the intensity of the upskilling or polarizing effect across sectors and firm size. Nevertheless, we could expect some heterogeneity of the ICT effect across industries and firm sizes. For instance, Stockinger (2019) finds that ICT diffusion in Germany leads to negative overall employment effects in manufacturing but positive effects in the service industries. Hence, we could expect to find more evidence of upskilling or polarization in firms that operate in the service sector rather than in manufacturing. Furthermore, the current debate on the role of ICT in the demand for skilled workers neglects possible heterogeneity across firm size. However, from a historical perspective, studies show that productivity gains derived from technological change increase relative to the size of the firm (Katz & Margo, 2014). We thus expect ICT to have a greater effect on labor demand in large firms than in small ones, due to the higher degree of division of labor.

Table 4 reports the coefficients of ICT for the different subsamples. In the first line, we report the *ICT* coefficients for the full sample, which represents our baseline. In the subsequent rows, we report the *ICT* coefficients estimated on subsamples by sector and firm size. To facilitate the comparison across subsamples, we report the coefficient for *ICT* and the number of cells including firms with those characteristics. The full tables, which include the coefficients for all regressors, are shown in "Appendix A.1."

We focus first on estimations by sector. By comparing the *ICT* coefficients with the one for the full sample, we observe that our measures of *ICT* suggest an upskilling effect for the manufacturing and service sectors, with the size of the effects larger in the former. Thus, our

Table 4 Pseudo-panel FE estimations: subsamples

	(1) Untrained	(2) VET	(3) High school	(4) PET	(5) UAS	(6) University
Full sample						
ICT	− 0.0983*** (0.0252)	− 0.188*** (0.0307)	0.0299** (0.0126)	0.0569** (0.0221)	0.120*** (0.0178)	0.0797*** (0.0254)
N	48386	48386	48386	48386	48386	48386
Subsamples by sector						
Manufacturing sector						
ICT	− 0.153** (0.0683)	− 0.264*** (0.0543)	0.00239 (0.0175)	0.0821*** (0.0301)	0.203*** (0.0356)	0.129*** (0.0287)
N	22473	22473	22473	22473	22473	22473
Service sector						
ICT	− 0.0890*** (0.0251)	− 0.155*** (0.0344)	0.0386*** (0.0148)	0.0521* (0.0267)	0.0914*** (0.0204)	0.0614** (0.0310)
N	26538	26538	26538	26538	26538	26538
Subsamples by firm size						
Small-sized firms						
ICT	− 0.0828*** (0.0296)	− 0.189*** (0.0369)	0.0247** (0.0117)	0.0506* (0.0273)	0.133*** (0.0227)	0.0637** (0.0306)
N	34173	34173	34173	34173	34173	34173
Medium-sized firms						
ICT	− 0.137** (0.0558)	− 0.103* (0.0608)	0.00771 (0.0157)	0.0974** (0.0394)	0.0442* (0.0257)	0.0909* (0.0516)
N	10422	10422	10422	10422	10422	10422
Large firms						
ICT	− 0.130 (0.0947)	− 0.283** (0.111)	0.155 (0.103)	0.0426 (0.0390)	0.0898* (0.0517)	0.126 (0.0921)
N	3791	3791	3791	3791	3791	3791

The table shows OLS coefficients of fixed effects estimates of a firm pseudo-panel with cells defined based on MS-region, industry, and firm size. Standard errors in parentheses are clustered at the cell level. *N* reports the number of pseudo-panel cells that contain at least one firm. The main explanatory variable measures the cell percentage of ICT workers according to ICT tasks (1996–2010) or ICT occupations (2012–2018). Estimates further control for time*MS-region fixed effects and cell averages of total employment, tenure, age, part-time status, and gender. Each column shows the results for a different dependent variable measuring the percentage of workers with a particular education within the cell

*$P < 0.10$, ** $P < 0.05$, ***$P < 0.01$

estimations cannot support the expectation that the size of the upskilling or polarizing effect of ICT is greater in the service sector.

We turn now to the estimation by firm size reported in the lower part of Table 4. The results show that the effects of ICT on the demand for workers with different education levels differ strongly across firm size. We observe generally larger effects in large firms than in medium or small ones. In small and medium firms, the patterns are consistent with the upskilling hypothesis, while in large firms the results are mixed. Hence, our expectation that the size of the upskilling or polarizing effect of ICT is greater in large firms than in small or medium ones is not confirmed.

6.2 GMM estimation

Table 5 reports the results of the GMM for 1996–2018. The GMM estimates suggest a positive but statistically insignificant coefficient for *ICT* on the demand for University workers. In contrast, the coefficients for UAS and PET workers are positive and statistically different from zero. The coefficient for UAS is slightly lower than that for the fixed effect estimation in Table 3, while that for PET is higher. Similarly, the coefficient for High school workers is higher in the GMM estimates than in the fixed effect estimation. The effect of ICT on the demand for VET workers is negative and statistically significant, albeit smaller than in the fixed effect estimations. Finally,

Table 5 GMM estimations

	(1) Untrained	(2) VET	(3) High school	(4) PET	(5) UAS	(6) University
ICT	− 0.118** (0.0464)	− 0.135** (0.0613)	0.0476* (0.0265)	0.0746** (0.0368)	0.0836** (0.0327)	0.0406 (0.0460)
Firm total employment	0.00000718* (0.00000394)	− 0.0000101** (0.00000456)	0.000000316 (0.000000949)	0.00000331 (0.00000305)	0.00000106 (0.00000162)	− 0.00000228 (0.00000280)
Tenure	− 0.00465** (0.00216)	0.00626** (0.00249)	0.0000152 (0.000634)	0.00166 (0.00127)	− 0.000893 (0.00106)	− 0.00286*** (0.00104)
Tenure squared	0.0000412 (0.0000710)	− 0.000149* (0.0000833)	0.0000114 (0.0000216)	− 0.00000692 (0.0000415)	0.0000403 (0.0000339)	0.0000772** (0.0000323)
Age	0.00801* (0.00486)	− 0.0213*** (0.00544)	− 0.00559*** (0.00184)	0.00330 (0.00279)	0.00394* (0.00221)	0.0127*** (0.00262)
Age squared	− 0.0000397 (0.0000595)	0.000234*** (0.0000666)	0.0000504** (0.0000219)	− 0.0000467 (0.0000339)	− 0.0000500* (0.0000281)	− 0.000158*** (0.0000330)
Part-time dummy	0.0622*** (0.0140)	− 0.0504*** (0.0151)	0.0123*** (0.00426)	− 0.0300*** (0.00764)	0.00659 (0.00597)	0.00174 (0.00761)
Male	0.00905 (0.0169)	0.0968*** (0.0193)	− 0.00189 (0.00596)	− 0.00998 (0.0103)	− 0.0583*** (0.00897)	− 0.0316*** (0.00894)
Time * MS-region FE	✓	✓	✓	✓	✓	✓
N	25838	25838	25838	25838	25838	25838
Mean dependent variable	0.213	0.552	0.0267	0.0966	0.0545	0.0570

The table shows the GMM estimates of a firm pseudo-panel with cells defined according to MS-region, industry, and firm size. Standard errors in parentheses are clustered at the cell level. *N* reports the number of pseudo-panel cells that contain at least one firm. The main explanatory variable measures the cell percentage of ICT workers according to ICT tasks (1996–2010) or according to ICT occupations (2012–2018). Estimates further control for time*MS-region fixed effects and cell averages of total employment, tenure, age, part-time status and gender. Each column shows the results for a different dependent variable measuring the percentage of workers with a particular education within the cell

*$P < 0.10$, ** $P < 0.05$, ***$P < 0.01$

the size of the *ICT* coefficient for VET workers is very close to that in the fixed effect estimation. Overall, the GMM estimations confirm the upskilling pattern previously observed.

7 Robustness check

This section deals with the issue of having two proxies for ICT occupations, one for 1996–2010 and the other for 2012–2018. Although Sect. 5 discusses the methodological concepts motivating the use of these variables and argues for the compatibility of these two measures, the question remains whether ICT's effect on the demand for labor might depend on the way the ICT variable is defined. Therefore, as a robustness check, we separately present the results for 1996–2010 and 2012–2018.

7.1 Fixed effect estimates for separate time periods

Tables 6 and 7 report the results based on the pseudo-panel procedure for the periods 1996–2010 and 2012–2018, respectively. As with the full sample, columns (1) to (6) use as dependent variables the percentages of the six educational groups that this paper uses.

The coefficient for *ICT* in column (6) for 1996–2010 is positive, statistically significant, and very close to those observed for the entire period. The coefficient for 2012–2018 is positive but not statistically different from zero. The coefficients in columns (5) are positive and statistically significant for both periods. The effect is larger in 1996–2010 than in 2012–2018. For both periods, the effect of *ICT* is thus larger for UAS workers than University ones. The coefficients for *ICT* in columns (4) are very similar and close to those for the entire period, even though the coefficient for 2012–2018 is not statistically significant.

The coefficients of *ICT* in column (3) in both samples are positive but not statistically different from zero. However, the size of the coefficients is similar to that observed in column (3) of Table 3. The *ICT* coefficients in columns (2) are negative and statistically significant for both samples, confirming ICT's negative effect on the demand for VET workers observed for the entire sample. Finally, the *ICT* coefficients in columns (1) indicate a negative effect for Untrained workers, which is larger—and statistically

Table 6 Pseudo-panel FE estimations: 1996–2010

	(1) Untrained	(2) VET	(3) High school	(4) PET	(5) UAS	(6) University
ICT (tasks-based)	− 0.189*** (0.0389)	− 0.0951* (0.0526)	0.0371 (0.0270)	0.0591* (0.0311)	0.116*** (0.0326)	0.0723** (0.0300)
Firm total employment	0.0000157*** (0.00000592)	− 0.0000128** (0.00000531)	− 0.00000210 (0.00000186)	0.000000508 (0.00000280)	9.01e−09 (0.000000942)	− 0.00000127 (0.00000116)
Tenure	− 0.00498*** (0.00167)	0.00797*** (0.00190)	0.000187 (0.000412)	0.000358 (0.000966)	− 0.000872 (0.000744)	− 0.00266*** (0.000633)
Tenure squared	0.0000713 (0.0000594)	− 0.000149** (0.0000666)	0.00000101 (0.0000135)	− 0.0000101 (0.0000319)	0.0000321 (0.0000237)	0.0000548** (0.0000215)
Age	0.00761** (0.00366)	− 0.0291*** (0.00417)	− 0.00141 (0.00118)	0.00994*** (0.00235)	0.00556*** (0.00158)	0.00741*** (0.00191)
Age squared	− 0.0000292 (0.0000454)	0.000296*** (0.0000519)	0.00000712 (0.0000142)	− 0.000120*** (0.0000293)	− 0.0000687*** (0.0000196)	− 0.0000845*** (0.0000254)
Part-time dummy	0.0390*** (0.00942)	− 0.0174* (0.0103)	0.00347 (0.00268)	− 0.0262*** (0.00512)	0.00293 (0.00433)	− 0.00181 (0.00388)
Male	0.0581*** (0.0124)	− 0.00676 (0.0136)	0.00498 (0.00345)	− 0.0262*** (0.00749)	− 0.0227*** (0.00590)	− 0.00743 (0.00521)
Time * MS-region FE	✓	✓	✓	✓	✓	✓
N	30628	30628	30628	30628	30628	30628
Mean dependent variable	0.241	0.568	0.0174	0.0855	0.0480	0.0405

The table shows OLS coefficients of fixed effects estimates of a firm pseudo-panel with cells defined based on MS-region, industry, and firm size. Standard errors in parentheses are clustered at the cell level. *N* reports the number of pseudo-panel cells that contain at least one firm. The main explanatory variable measures the cell percentage of ICT workers according to ICT tasks. Estimates further control for time* MS-region fixed effects and cell averages of total employment, tenure, age, part-time status and gender. Each column shows the results for a different dependent variable measuring the percentage of workers with a particular education within the cell

*$P < 0.10$, ** $P < 0.05$, ***$P < 0.01$

significant—for 1996–2010, but not statistically different from zero for 2012–2018.

The comparison of the values for *ICT* across the two periods suggests similar patterns for some education groups, but different effects for others. The effect on the demand for workers with UAS, PET, High school, or VET as the highest level of education is similar in both periods. In contrast, the effect of ICT on the demand for University or Untrained workers differs across the two periods. Nevertheless, the patterns for both periods are more in line with the upskilling hypothesis (H1a) than the job polarization hypothesis (H1b).

7.2 GMM estimates for separate time periods

Tables 8 and 9 report the results of the GMM for 1996–2010 and 2012–2016, respectively. Compared to the pseudo-panel FE estimates presented in Tables 6 and 7, the GMM additionally accounts for potential reverse causality by instrumenting variables by the corresponding lagged values and differences (Arellano & Bond, 1991).

The GMM estimates for 1996–2010 suggest a significant positive coefficient for *ICT* on the demand for University and UAS workers. These coefficients are slightly higher than those for the fixed effect estimation presented in Table 6. In contrast to the fixed effect estimation, the GMM coefficient of *ICT* for PET workers is no longer statistically significant, while that for High school workers is statistically significant. Finally, the sizes of *ICT* coefficients for VET and Untrained workers are close to those in the fixed effect estimation. Overall, the GMM estimations confirm the upskilling pattern previously observed.

The GMM estimates for 2012–2018, reported in Table 9, present no significant effect of ICT on any education group. Although the direction of the coefficients resembles the pattern observed in Table 7, we cannot provide evidence that ICT affects the percentage of workers with a given education in 2012–2018. Extending the time period would probably allow us to obtain more precise estimations.

Table 7 Pseudo-panel FE estimations: 2012–2018

	(1) Untrained	(2) VET	(3) High school	(4) PET	(5) UAS	(6) University
ICT (occupations-based)	− 0.0609 (0.0396)	− 0.103** (0.0425)	0.0199 (0.0238)	0.0465 (0.0380)	0.0701* (0.0359)	0.0274 (0.0297)
Firm total employment	0.00000624** (0.00000268)	− 0.00000585* (0.00000325)	0.000000172 (0.000000787)	− 0.000000116 (0.000000851)	− 0.000000618 (0.000000637)	0.000000170 (0.00000111)
Tenure	− 0.00932*** (0.00201)	0.00803*** (0.00249)	− 0.00145 (0.000970)	0.00315** (0.00144)	− 0.000277 (0.00108)	− 0.000132 (0.00138)
Tenure squared	0.000213*** (0.0000681)	− 0.000199** (0.0000797)	0.0000499 (0.0000329)	− 0.0000353 (0.0000488)	0.0000118 (0.0000380)	− 0.0000407 (0.0000430)
Age	0.00596 (0.00463)	− 0.0244*** (0.00574)	− 0.00811*** (0.00230)	0.00744** (0.00308)	0.00890*** (0.00258)	0.0102*** (0.00309)
Age squared	− 0.0000254 (0.0000561)	0.000262*** (0.0000689)	0.0000790*** (0.0000267)	− 0.0000897** (0.0000372)	− 0.000107*** (0.0000321)	− 0.000119*** (0.0000381)
Part-time dummy	0.0221 (0.0152)	− 0.0109 (0.0177)	0.00951 (0.00648)	− 0.0277*** (0.00938)	0.0207*** (0.00798)	− 0.0137 (0.00922)
Male	0.0327* (0.0174)	0.0133 (0.0202)	0.00440 (0.00799)	− 0.0159 (0.0105)	− 0.0319*** (0.00970)	− 0.00252 (0.0110)
Time * MS-region FE	✓	✓	✓	✓	✓	✓
N	17747	17747	17747	17747	17747	17747
Mean dependent variable	0.191	0.528	0.0380	0.103	0.0630	0.0768

The table shows OLS coefficients of fixed effects estimates of a firm pseudo-panel with cells defined based on MS-region, industry, and firm size. Standard errors in parentheses are clustered at the cell level. *N* reports the number of pseudo-panel cells that contain at least one firm. The main explanatory variable measures the cell percentage of ICT workers according to ICT occupations. Estimates further control for MS-region*time fixed effects and cell averages of total employment, tenure, age, part-time status, and gender. Each column shows the results for a different dependent variable measuring the percentage of workers with a particular education within the cell

*$P < 0.10$, ** $P < 0.05$, ***$P < 0.01$

Table 8 GMM estimations: 1996–2010

	(1) Untrained	(2) VET	(3) High school	(4) PET	(5) UAS	(6) University
ICT (tasks-based)	− 0.275*** (0.0753)	− 0.0827 (0.0947)	0.0809** (0.0409)	0.0295 (0.0601)	0.141*** (0.0452)	0.0918*** (0.0348)
Firm total employment	0.00000963** (0.00000473)	− 0.00000696 (0.00000544)	− 0.00000187 (0.00000178)	0.00000321 (0.00000505)	− 0.00000201 (0.00000190)	− 0.00000342 (0.00000241)
Tenure	− 0.000508 (0.00281)	0.00215 (0.00316)	− 0.000742 (0.000695)	0.000508 (0.00161)	− 0.000886 (0.00133)	− 0.000775 (0.000990)
Tenure squared	− 0.0000950 (0.0000950)	− 0.00000906 (0.000109)	0.0000371* (0.0000220)	0.00000966 (0.0000528)	0.0000514 (0.0000414)	0.0000153 (0.0000324)
Age	0.000754 (0.00639)	− 0.0136* (0.00703)	0.000736 (0.00192)	0.00150 (0.00391)	0.00285 (0.00279)	0.00836*** (0.00293)
Age squared	0.0000550 (0.0000791)	0.000128 (0.0000874)	− 0.0000191 (0.0000233)	− 0.0000277 (0.0000484)	− 0.0000379 (0.0000373)	− 0.000106*** (0.0000392)
Part-time dummy	0.0589*** (0.0176)	− 0.0666*** (0.0182)	0.0179*** (0.00411)	− 0.0270*** (0.00829)	0.0141** (0.00703)	0.00596 (0.00778)
Male	0.0881*** (0.0264)	0.0198 (0.0295)	− 0.00740 (0.00621)	− 0.0676*** (0.0162)	− 0.0176 (0.0128)	− 0.00966 (0.00902)
Time * MS-region FE	✓	✓	✓	✓	✓	✓
N	16290	16290	16290	16290	16290	16290
Mean dependent variable	0.229	0.573	0.0190	0.0909	0.0465	0.0420

The table shows the GMM estimates of a firm pseudo-panel with cells defined according to MS-region, industry, and firm size. Standard errors in parentheses are clustered at the cell level. *N* reports the number of pseudo-panel cells that contain at least one firm. The main explanatory variable measures the cell percentage of ICT workers according to ICT tasks. Estimates further control for time*MS-region fixed effects and cell averages of total employment, tenure, age, part-time status, and gender. Each column shows the results for a different dependent variable measuring the percentage of workers with a particular education within the cell

*$P < 0.10$, ** $P < 0.05$, ***$P < 0.01$

Table 9 GMM estimations: 2012–2018

	(1) Untrained	(2) VET	(3) High school	(4) PET	(5) UAS	(6) University
ICT (occupation-based)	0.00800 (0.0889)	− 0.133 (0.111)	0.00972 (0.0469)	− 0.00685 (0.0716)	0.102 (0.0768)	0.0157 (0.0658)
Firm total employment	0.000000672 (0.00000426)	− 0.0000133** (0.00000581)	0.000000792 (0.00000160)	0.00000518 (0.00000372)	0.00000678* (0.00000382)	− 6.91e−08 (0.00000366)
Tenure	− 0.0121*** (0.00398)	0.00913* (0.00469)	− 0.000484 (0.00156)	0.00320 (0.00246)	0.000893 (0.00202)	− 0.00123 (0.00220)
Tenure squared	0.000275** (0.000122)	− 0.000202 (0.000147)	− 0.0000312 (0.0000516)	− 0.0000174 (0.0000794)	− 0.0000658 (0.0000641)	0.0000550 (0.0000683)
Age	0.0134 (0.00852)	− 0.0242** (0.00941)	− 0.0124*** (0.00347)	0.00640 (0.00483)	0.0126*** (0.00383)	0.00477 (0.00417)
Age squared	− 0.0000941 (0.000103)	0.000264** (0.000115)	0.000133*** (0.0000403)	− 0.0000786 (0.0000584)	− 0.000152*** (0.0000480)	− 0.0000772 (0.0000506)
Part− time dummy	0.0298 (0.0274)	− 0.0250 (0.0323)	0.0135 (0.0115)	− 0.0327* (0.0168)	− 0.00166 (0.0147)	0.0219 (0.0148)
Male	0.0566* (0.0295)	− 0.00200 (0.0349)	− 0.0138 (0.0129)	− 0.0221 (0.0197)	− 0.00933 (0.0149)	− 0.00899 (0.0177)
Time * MS-region FE	✓	✓	✓	✓	✓	✓
N	6952	6952	6952	6952	6952	6952
Mean dependent variable	0.185	0.521	0.0391	0.110	0.0654	0.0793

The table shows the GMM estimates of a firm pseudo-panel with cells defined according to MS-region, industry, and firm size. Standard errors in parentheses are clustered at the cell level. *N* reports the number of pseudo-panel cells that contain at least one firm. The main explanatory variable measures the cell percentage of ICT workers according to ICT occupations. Estimates further control for time*MS-region fixed effects and cell averages of total employment, tenure, age, part-time status, and gender. Each column shows the results for a different dependent variable measuring the percentage of workers with a particular education within the cell

$^*P < 0.10$, $^{**} P < 0.05$, $^{***}P < 0.01$

8 Conclusion

This paper explores hypotheses concerning skills-biased technical change and job polarization in Switzerland. Specifically, we estimate the effect of ICT on the demand for workers with VET and PET degrees. Whereas most studies on the impact of technological change on the labor market only compare tertiary-educated versus non-tertiary-educated workers, we add to this literature by differentiating between six levels of worker education. In addition to untrained workers, high school graduates, and academic university-educated workers, our novel analysis also differentiates workers with an upper secondary VET education, a tertiary PET degree, and a UAS degree. The addition of these three groups is highly valuable for countries such as Austria, Denmark, Germany, and Switzerland—with their large vocationally educated workforce—and for countries in the process of adopting or considering adopting dual VET programs.

Our results suggest that ICT had an upskilling effect during 1996–2018, meaning that ICT decreased the demand for untrained workers and those with an upper secondary VET education, while it increased the demand for tertiary-educated workers, especially those with a UAS degree. The positive effect on the demand for workers with tertiary professional education means that there is still a need for people with VET as their initial education because these are the main providers of PET and UAS. Therefore, our results show that upper secondary VET as a stepping stone to a UAS education is vital for both the manufacturing and service sectors. The results suggest that VET is a valid and valuable alternative to a strictly academic education, because workers with a tertiary VET degree are highly competitive in the job market and adjust well to technological change.

This paper has several limitations that should be remedied in future research. First, our estimations are based on survey data, which might include measurement errors. Future research using administrative data could avoid random and systematic measurement errors. Second, our measure of ICT—which considers the percentage of ICT workers within firms—reflects only a particular type of ICT intensity. Different ICT investments might affect a firm's business practices and skill demand and might even interact (Kaiser, 2003). Unfortunately, the dataset used in the current analysis does not offer the possibility of testing other types of ICT. Future research should try to close this gap by testing different types of ICT.

Most importantly, future research should apply the approach developed in this paper to other countries with formal VET programs, especially because the adaptability of VET-educated workers to technological change has high priority in policy reforms aimed at aligning education with labor market needs. This close relationship between a VET education and labor market is particularly apparent in Switzerland, where VET and PET profiles are developed in close collaboration with the Swiss economy. However, countries with different VET programs and specific labor market needs will probably differ in terms of polarization and upskilling.

Another limitation is that our empirical strategy does not account for policy changes. For instance, the opening toward cross-border workers during the 2000s could have affected the proportion of ICT workers and the proportion of workers with a specific education. The fact that results from estimations on different subperiods indicate a certain consistency over time provides some indirect evidence that policy changes might not have driven the results, though. Nevertheless, our results might still be biased by unobserved factors correlated with ICT adoption, such as other policy reforms that could have increased the demand for ICT workers and workers with tertiary education simultaneously. Such reforms would weaken the causal interpretation of our findings.

A Appendix

A.1 Main results by subsamples

See Tables 10, 11, 12, 13, 14, 15, 16, and 17.

Table 10 Pseudo-panel FE estimates for 1996–2018: small-sized firms

	(1) **Untrained**	(2) **VET**	(3) **High school**	(4) **PET**	(5) **UAS**	(6) **University**
ICT	− 0.0828*** (0.0296)	− 0.189*** (0.0369)	0.0247** (0.0117)	0.0506* (0.0273)	0.133*** (0.0227)	0.0637** (0.0306)
Firm total employment	0.00189*** (0.000200)	− 0.00211*** (0.000226)	0.000110* (0.0000645)	− 0.000443*** (0.000116)	0.000272*** (0.0000975)	0.000274** (0.000111)
Tenure	− 0.00531*** (0.00138)	0.00717*** (0.00164)	− 0.000124 (0.000481)	0.00189** (0.000867)	− 0.000855 (0.000667)	− 0.00277*** (0.000735)
Tenure squared	0.0000838* (0.0000484)	− 0.000145*** (0.0000555)	0.0000107 (0.0000161)	− 0.0000345 (0.0000296)	0.0000432* (0.0000225)	0.0000414* (0.0000229)
Age	0.00671** (0.00294)	− 0.0232*** (0.00348)	− 0.00406*** (0.00114)	0.00596*** (0.00192)	0.00497*** (0.00143)	0.00957*** (0.00185)
Age squared	− 0.0000305 (0.0000360)	0.000234*** (0.0000426)	0.0000350*** (0.0000135)	− 0.0000715*** (0.0000237)	− 0.0000606*** (0.0000178)	− 0.000106*** (0.0000236)
Part-time dummy	0.0279*** (0.00871)	− 0.0391*** (0.0101)	0.00984*** (0.00309)	− 0.0266*** (0.00519)	0.0218*** (0.00488)	0.00626 (0.00507)
Male	0.00481 (0.0102)	0.0522*** (0.0119)	0.00870** (0.00338)	− 0.00491 (0.00594)	− 0.0407*** (0.00618)	− 0.0201*** (0.00578)
Time * MS-region FE	✓	✓	✓	✓	✓	✓
N	34173	34173	34173	34173	34173	34173
Mean dependent variable	0.211	0.573	0.0260	0.0910	0.0503	0.0492

The table shows OLS coefficients of fixed effects estimates of a firm pseudo-panel with cells defined based on MS-region, industry, and firm size. Standard errors in parentheses are clustered at the cell level. *N* reports the number of pseudo-panel cells that contain at least one firm. The main explanatory variable measures the cell percentage of ICT workers according to ICT tasks (1996–2010) or ICT occupations (2012–2018). Estimates further control for time*MS-region fixed effects and cell averages of total employment, tenure, age, part-time status, and gender. Each column shows the results for a different dependent variable measuring the percentage of workers with a particular education within the cell

*$P < 0.10$, ** $P < 0.05$, ***$P < 0.01$

Table 11 Pseudo-panel FE estimates for 1996–2018: medium-sized firms

	(1) **Untrained**	(2) **VET**	(3) **High school**	(4) **PET**	(5) **UAS**	(6) **University**
ICT	− 0.137** (0.0558)	− 0.103* (0.0608)	0.00771 (0.0157)	0.0974** (0.0394)	0.0442* (0.0257)	0.0909* (0.0516)
Firm total employment	0.0000830 (0.0000592)	− 0.0000578 (0.0000610)	− 0.00000588 (0.0000175)	− 0.0000249 (0.0000289)	− 0.0000309 (0.0000273)	0.0000364 (0.0000361)
Tenure	− 0.00464 (0.00382)	0.0161*** (0.00376)	− 0.000743 (0.00123)	0.000735 (0.00187)	− 0.00273* (0.00161)	− 0.00873*** (0.00227)
Tenure squared	0.0000567 (0.000128)	− 0.000532*** (0.000128)	0.0000416 (0.0000404)	− 0.0000131 (0.0000621)	0.000155*** (0.0000591)	0.000292*** (0.0000818)
Age	− 0.0129 (0.0112)	− 0.106*** (0.0114)	− 0.00542 (0.00419)	0.0222*** (0.00514)	0.0329*** (0.00441)	0.0688*** (0.00857)
Age squared	0.000212 (0.000137)	0.00128*** (0.000140)	0.0000436 (0.0000498)	− 0.000270*** (0.0000647)	− 0.000409*** (0.0000552)	− 0.000852*** (0.000104)
Part-time dummy	0.114*** (0.0199)	− 0.0974*** (0.0191)	0.00296 (0.00536)	− 0.0224*** (0.00831)	0.0267*** (0.00902)	− 0.0234** (0.0108)
Male	0.0778*** (0.0277)	− 0.0129 (0.0274)	0.00857 (0.00633)	− 0.0263** (0.0122)	− 0.0585*** (0.0117)	0.0113 (0.0160)
Time * MS-region FE	✓	✓	✓	✓	✓	✓
N	10422	10422	10422	10422	10422	10422
Mean dependent variable	0.251	0.508	0.0217	0.0954	0.0617	0.0620

The table shows OLS coefficients of fixed effects estimates of a firm pseudo-panel with cells defined based on MS-region, industry, and firm size. Standard errors in parentheses are clustered at the cell level. *N* reports the number of pseudo-panel cells that contain at least one firm. The main explanatory variable measures the cell percentage of ICT workers according to ICT tasks (1996–2010) or ICT occupations (2012–2018). Estimates further control for time*MS-region fixed effects and cell averages of total employment, tenure, age, part-time status, and gender. Each column shows the results for a different dependent variable measuring the percentage of workers with a particular education within the cell

*$P < 0.10$, ** $P < 0.05$, ***$P < 0.01$

Table 12 Pseudo-panel FE estimates for 1996–2018: large firms

	(1) **Untrained**	(2) **VET**	(3) **High school**	(4) **PET**	(5) **UAS**	(6) **University**
ICT	− 0.130 (0.0947)	− 0.283** (0.111)	0.155 (0.103)	0.0426 (0.0390)	0.0898* (0.0517)	0.126 (0.0921)
Firm total employment	0.0000102*** (0.00000240)	− 0.00000821*** (0.00000239)	− 0.000000479 (0.000000606)	0.000000758 (0.00000152)	− 0.000000484 (0.000000807)	− 0.00000174 (0.00000108)
Tenure	− 0.0183** (0.00903)	0.0102 (0.00934)	0.00547* (0.00326)	− 0.000162 (0.00302)	0.00259 (0.00396)	0.000265 (0.00440)
Tenure squared	0.000446 (0.000306)	− 0.000324 (0.000314)	− 0.0000986 (0.000119)	0.00000669 (0.000111)	− 0.000123 (0.000141)	0.0000920 (0.000149)
Age	0.0663** (0.0298)	− 0.171*** (0.0397)	− 0.00532 (0.0151)	0.0143 (0.0137)	0.0137 (0.0120)	0.0821*** (0.0221)
Age squared	− 0.000666* (0.000383)	0.00207*** (0.000484)	0.0000142 (0.000188)	− 0.000176 (0.000174)	− 0.000139 (0.000156)	− 0.00110*** (0.000274)
Part-time dummy	0.165*** (0.0433)	− 0.145*** (0.0480)	0.00139 (0.0127)	− 0.00282 (0.0171)	− 0.00235 (0.0133)	− 0.0160 (0.0205)
Male	0.0928 (0.0712)	− 0.0762 (0.0833)	0.0583** (0.0277)	0.00163 (0.0270)	− 0.0426* (0.0245)	− 0.0340 (0.0492)
Time * MS-region FE	✓	✓	✓	✓	✓	✓
N	3791	3791	3791	3791	3791	3791
Mean dependent variable	0.250	0.499	0.0247	0.0908	0.0624	0.0735

The table shows OLS coefficients of fixed effects estimates of a firm pseudo-panel with cells defined based on MS-region, industry, and firm size. Standard errors in parentheses are clustered at the cell level. *N* reports the number of pseudo-panel cells that contain at least one firm. The main explanatory variable measures the cell percentage of ICT workers according to ICT tasks (1996–2010) or ICT occupations (2012–2018). Estimates further control for time*MS-region fixed effects and cell averages of total employment, tenure, age, part-time status, and gender. Each column shows the results for a different dependent variable measuring the percentage of workers with a particular education within the cell

*$P < 0.10$, ** $P < 0.05$, ***$P < 0.01$

Table 13 Pseudo-panel FE estimates for 1996–2018: manufacturing sector firms

	(1) Untrained	(2) VET	(3) High school	(4) PET	(5) UAS	(6) University
ICT	− 0.153** (0.0683)	− 0.264*** (0.0543)	0.00239 (0.0175)	0.0821*** (0.0301)	0.203*** (0.0356)	0.129*** (0.0287)
Firm total employment	0.0000332** (0.0000135)	− 0.0000155 (0.0000160)	− 0.00000374 (0.00000361)	− 0.000000331 (0.00000769)	− 0.00000829 (0.00000664)	− 0.00000528 (0.00000504)
Tenure	0.00161 (0.00200)	0.00442** (0.00215)	− 0.000640 (0.000626)	− 0.000349 (0.00113)	− 0.00132** (0.000642)	− 0.00372*** (0.000740)
Tenure squared	− 0.0000375 (0.0000654)	− 0.000107 (0.0000698)	0.0000223 (0.0000211)	0.0000200 (0.0000372)	0.0000265 (0.0000209)	0.0000758*** (0.0000215)
Age	0.0182*** (0.00455)	− 0.0395*** (0.00513)	− 0.00239 (0.00154)	0.00795*** (0.00287)	0.00619*** (0.00161)	0.00959*** (0.00207)
Age squared	− 0.000180*** (0.0000553)	0.000429*** (0.0000623)	0.0000210 (0.0000183)	− 0.0000932*** (0.0000348)	− 0.0000677*** (0.0000200)	− 0.000109*** (0.0000258)
Part-time dummy	− 0.0156 (0.0118)	0.0345*** (0.0128)	0.0000692 (0.00355)	− 0.00662 (0.00635)	− 0.00452 (0.00394)	− 0.00780 (0.00481)
Male	0.0595*** (0.0158)	− 0.0677*** (0.0160)	0.0128*** (0.00430)	− 0.0127* (0.00748)	0.000388 (0.00476)	0.00774 (0.00534)
Time * MS-region FE	✓	✓	✓	✓	✓	✓
N	22473	22473	22473	22473	22473	22473
Mean dependent variable	0.269	0.558	0.0168	0.0870	0.0389	0.0301

The table shows OLS coefficients of fixed effects estimates of a firm pseudo-panel with cells defined based on MS-region, industry and firm size. Standard errors in parentheses are clustered at the cell level. *N* reports the number of pseudo-panel cells that contain at least one firm The main explanatory variable measures the cell percentage of ICT workers according to ICT tasks (1996–2010) or ICT occupations (2012–2018). Estimates further control for time*MS-region fixed effects and cell averages of total employment, tenure, age, part-time status, and gender Each column shows the results for a different dependent variable measuring the percentage of workers with a particular education within the cell

*$P < 0.10$, ** $P < 0.05$, ***$P < 0.01$

Table 14 Pseudo-panel FE estimates for 1996–2018: service sector firms

	(1) Untrained	(2) VET	(3) High school	(4) PET	(5) UAS	(6) University
ICT	− 0.0890*** (0.0251)	− 0.155*** (0.0344)	0.0386*** (0.0148)	0.0521* (0.0267)	0.0914*** (0.0204)	0.0614** (0.0310)
Firm total employment	0.0000112*** (0.00000211)	− 0.0000107*** (0.00000283)	− 0.000000124 (0.000000629)	− 1.50e−08 (0.00000126)	− 0.000000531 (0.000000796)	0.000000202 (0.00000105)
Tenure	− 0.00966*** (0.00163)	0.00847*** (0.00209)	0.000586 (0.000623)	0.00308*** (0.00112)	− 0.000943 (0.00105)	− 0.00153 (0.00113)
Tenure squared	0.000165*** (0.0000581)	− 0.000143* (0.0000756)	− 0.0000193 (0.0000212)	− 0.0000667 (0.0000406)	0.0000841** (0.0000405)	− 0.0000200 (0.0000400)
Age	− 0.00461 (0.00366)	− 0.0189*** (0.00439)	− 0.00623*** (0.00151)	0.00672*** (0.00239)	0.00664*** (0.00209)	0.0164*** (0.00277)
Age squared	0.000109** (0.0000448)	0.000196*** (0.0000540)	0.0000554*** (0.0000180)	− 0.0000811*** (0.0000302)	− 0.0000881*** (0.0000262)	− 0.000191*** (0.0000352)
Part-time dummy	0.0713*** (0.0106)	− 0.0723*** (0.0122)	0.0129*** (0.00384)	− 0.0370*** (0.00622)	0.0348*** (0.00638)	− 0.00962 (0.00721)
Male	0.000297 (0.0115)	0.108*** (0.0145)	0.00663 (0.00445)	− 0.00496 (0.00753)	− 0.0753*** (0.00821)	− 0.0348*** (0.00827)
Time * Region FE	✓	✓	✓	✓	✓	✓
N	26538	26538	26538	26538	26538	26538
Mean dependent variable	0.182	0.549	0.0319	0.0969	0.0662	0.0743

The table shows OLS coefficients of fixed effects estimates of a firm pseudo-panel with cells defined based on MS-region, industry, and firm size. Standard errors in parentheses are clustered at the cell level. *N* reports the number of pseudo-panel cells that contain at least one firm. The main explanatory variable measures the cell percentage of ICT workers according to ICT tasks (1996–2010) or ICT occupations (2012–2018). Estimates further control for time*MS-region fixed effects and cell averages of total employment, tenure, age, part-time status, and gender Each column shows the results for a different dependent variable measuring the percentage of workers with a particular education within the cell

*$P < 0.10$, ** $P < 0.05$, ***$P < 0.01$

Table 15 Pseudo-panel FE estimation. Cells based on two firm sizes instead of three sizes

	(1) Untrained	(2) VET	(3) High school	(4) PET	(5) UAS	(6) University
ICT	− 0.0907*** (0.0261)	− 0.192*** (0.0319)	0.0287*** (0.0109)	0.0536** (0.0234)	0.120*** (0.0187)	0.0801*** (0.0266)
Firm total employment	0.0000133*** (0.00000269)	− 0.0000115*** (0.00000240)	0.000000177 (0.000000473)	− 0.000000878 (0.000000991)	− 0.000000823 (0.000000861)	− 0.000000284 (0.00000132)
Tenure	− 0.00542*** (0.00131)	0.00738*** (0.00153)	− 0.0000765 (0.000450)	0.00178** (0.000797)	− 0.000871 (0.000626)	− 0.00278*** (0.000690)
Tenure squared	0.0000909** (0.0000456)	− 0.000158*** (0.0000520)	0.0000105 (0.0000152)	− 0.0000357 (0.0000273)	0.0000492** (0.0000214)	0.0000435** (0.0000219)
Age	0.00686** (0.00287)	− 0.0283*** (0.00335)	− 0.00413*** (0.00109)	0.00638*** (0.00183)	0.00639*** (0.00137)	0.0128*** (0.00182)
Age squared	− 0.0000324 (0.0000352)	0.000298*** (0.0000410)	0.0000352*** (0.0000129)	− 0.0000760*** (0.0000226)	− 0.0000782*** (0.0000172)	− 0.000147*** (0.0000232)
Part-time dummy	0.0351*** (0.00800)	− 0.0366*** (0.00890)	0.00825*** (0.00268)	− 0.0248*** (0.00445)	0.0206*** (0.00431)	− 0.00258 (0.00468)
Male	0.0100 (0.00959)	0.0459*** (0.0109)	0.00857*** (0.00309)	− 0.00683 (0.00533)	− 0.0428*** (0.00564)	− 0.0149*** (0.00553)
Time * MS-region FE	✓	✓	✓	✓	✓	✓
N	45807	45807	45807	45807	45807	45807
Mean dependent variable	0.222	0.556	0.0250	0.0915	0.0529	0.0527

The table shows OLS coefficients of fixed effects estimates of a firm pseudo-panel with cells defined based on MS-region, industry, and firm size. Standard errors in parentheses are clustered at the cell level. *N* reports the number of pseudo-panel cells that contain at least one firm. The main explanatory variable measures the cell percentage of ICT workers according to ICT tasks (1996–2010) or ICT occupations (2012–2018). Estimates further control for time*MS-region fixed effects and cell averages of total employment, tenure, age, part-time status, and gender. Each column shows the results for a different dependent variable measuring the percentage of workers with a particular education within the cell

*$P < 0.10$, ** $P < 0.05$, ***$P < 0.01$

Table 16 Pseudo-panel FE estimation. Cells based on 16 supra-regional labor market instead of 106 local labor market regions (MS-regions)

	(1) Untrained	(2) VET	(3) High school	(4) PET	(5) UAS	(6) University
ICT	− 0.119*** (0.0425)	− 0.221*** (0.0557)	0.0391* (0.0209)	0.0871*** (0.0333)	0.172*** (0.0317)	0.0417 (0.0369)
Firm total employment	0.00000529* (0.00000306)	− 0.00000628** (0.00000286)	− 0.000000337 (0.000000700)	0.000000239 (0.00000102)	− 6.06e−08 (0.000000711)	0.00000115 (0.00000104)
Tenure	− 0.00843*** (0.00303)	0.00880*** (0.00315)	0.000500 (0.00114)	0.00448*** (0.00154)	− 0.00105 (0.00122)	− 0.00429*** (0.00154)
Tenure squared	0.000152 (0.000111)	− 0.000180 (0.000114)	0.0000113 (0.0000409)	− 0.000137*** (0.0000522)	0.0000523 (0.0000426)	0.000102** (0.0000501)
Age	0.0102 (0.00778)	− 0.0616*** (0.00846)	− 0.00358 (0.00290)	0.00311 (0.00480)	0.0128*** (0.00358)	0.0391*** (0.00601)
Age squared	− 0.0000507 (0.0000986)	0.000716*** (0.000106)	0.0000119 (0.0000345)	− 0.0000326 (0.0000609)	− 0.000160*** (0.0000430)	− 0.000484*** (0.0000769)
Part-time dummy	0.0894*** (0.0169)	− 0.106*** (0.0167)	0.0221*** (0.00597)	− 0.0189** (0.00748)	0.0258*** (0.00772)	− 0.0123 (0.00963)
Male	0.0216 (0.0207)	0.0228 (0.0205)	0.0114 (0.00718)	− 0.00451 (0.00929)	− 0.0436*** (0.00912)	− 0.00763 (0.0118)
Time * Supra-region FE	✓	✓	✓	✓	✓	✓
N	14181	14181	14181	14181	14181	14181
Mean dependent variable	0.246	0.507	0.0306	0.0901	0.0573	0.0682

Cells based on 16 supra-regional labor market instead of 106 local labor market regions (MS-regions)

The table shows OLS coefficients of fixed effects estimates of a firm pseudo-panel with cells defined based on supra-regional labor market, industry, and firm size. Standard errors in parentheses are clustered at the cell level. *N* reports the number of pseudo-panel cells that contain at least one firm. The main explanatory variable measures the cell percentage of ICT workers according to ICT tasks (1996–2010) or ICT occupations (2012–2018). Estimates further control for time*supra-region fixed effects and cell averages of total employment, tenure, age, part-time status, and gender. Each column shows the results for a different dependent variable measuring the percentage of workers with a particular education within the cell

*$P < 0.10$, ** $P < 0.05$, ***$P < 0.01$

Table 17 Pseudo-panel FE estimation. Cells based on 18 branches instead of two-digit industries

	(1) Untrained	(2) VET	(3) High school	(4) PET	(5) UAS	(6) University
ICT	− 0.171*** (0.0288)	− 0.292*** (0.0333)	0.0774*** (0.0204)	0.0918*** (0.0197)	0.133*** (0.0226)	0.162*** (0.0253)
Firm total employment	0.00000545** (0.00000246)	− 0.00000621*** (0.00000152)	− 0.000000284 (0.000000360)	0.000000207 (0.00000138)	0.000000413 (0.000000736)	0.000000426 (0.000000673)
Tenure	− 0.0108*** (0.00181)	0.00656*** (0.00204)	0.000641 (0.000595)	0.00287*** (0.00105)	0.000781 (0.000910)	− 0.0000238 (0.000945)
Tenure squared	0.000175*** (0.0000648)	− 0.0000797 (0.0000723)	− 0.0000197 (0.0000205)	− 0.0000421 (0.0000353)	0.00000890 (0.0000322)	− 0.0000428 (0.0000329)
Age	0.00438 (0.00402)	− 0.0321*** (0.00470)	− 0.00455*** (0.00131)	0.0123*** (0.00233)	0.00945*** (0.00194)	0.0105*** (0.00260)
Age squared	0.0000113 (0.0000491)	0.000334*** (0.0000577)	0.0000422*** (0.0000156)	− 0.000155*** (0.0000290)	− 0.000117*** (0.0000246)	− 0.000117*** (0.0000341)
Part-time dummy	0.0550*** (0.0105)	− 0.0527*** (0.0113)	0.0156*** (0.00306)	− 0.0287*** (0.00550)	0.0179*** (0.00564)	− 0.00704 (0.00565)
Male	0.0339*** (0.0126)	0.0402*** (0.0147)	0.00147 (0.00423)	− 0.0270*** (0.00712)	− 0.0295*** (0.00760)	− 0.0191** (0.00748)
Time * MS-region FE	✓	✓	✓	✓	✓	✓
N	26358	26358	26358	26358	26358	26358
Mean dependent variable	0.218	0.545	0.0256	0.0923	0.0618	0.0570

Cells based on 18 branches instead of two-digit industries

The table shows OLS coefficients of fixed effects estimates of a firm pseudo-panel with cells defined based on MS-region, branches, and firm size. Standard errors in parentheses are clustered at the cell level. *N* reports the number of pseudo-panel cells that contain at least one firm. The main explanatory variable measures the cell percentage of ICT workers according to ICT tasks (1996–2010) or ICT occupations (2012–2018). Estimates further control for time*MS-region fixed effects and cell averages of total employment, tenure, age, part-time status, and gender. Each column shows the results for a different dependent variable measuring the percentage of workers with a particular education within the cell

*$P < 0.10$, ** $P < 0.05$, ***$P < 0.01$

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Author Contributions
FP conducted the data curation and formal analysis. UR supervised the project. All authors contributed to the methodology and were engaged in writing and editing of the manuscript. All authors read and approved the final manuscript.

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Availability of data and materials
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Declarations

Competing interests
The authors declare no competing interests.

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References

Acemoglu, D. (1999). Changes in unemployment and wage inequality: An alternative theory and some evidence. *American Economic Review, 89*(5), 1259–1278.

Acemoglu, D. (2002). Technical change, inequality, and the labor market. *Journal of Economic Literature, 40*(1), 7–72.

Acemoglu, D. & Autor, D. (2011). Skills, tasks and technologies: Implications for employment and earnings. In *Handbook of labor economics*, volume 4 (pp. 1043–1171). Elsevier.

Antman, F., & McKenzie, D. J. (2007). Earnings mobility and measurement error: A pseudo-panel approach. *Economic Development and Cultural Change, 56*(1), 125–161.

Arellano, M., & Bond, S. (1991). Some tests of specification for panel data: Monte carlo evidence and an application to employment equations. *The Review of Economic Studies, 58*(2), 277–297.

Arvanitis, S. (2005). Computerization, workplace organization, skilled labour and firm productivity: Evidence for the swiss business sector. *Economics of Innovation and New Technology, 14*(4), 225–249.

Arvanitis, S., & Loukis, E. N. (2009). Information and communication technologies, human capital, workplace organization and labour productivity: A comparative study based on firm-level data for greece and switzerland. *Information Economics and Policy, 21*(1), 43–61.

Autor, D. H., Dorn, D., & Hanson, G. H. (2015). Untangling trade and technology: Evidence from local labour markets. *The Economic Journal, 125*(584), 621–646.
Autor, D. H., Katz, L. F., & Kearney, M. S. (2006). The polarization of the us labor market. *The American Economic Review, 96*(2), 189–194.
Autor, D. H., Katz, L. F., & Krueger, A. B. (1998). Computing inequality: Have computers changed the labor market? *The Quarterly Journal of Economics, 113*(4), 1169–1213.
Autor, D. H., Levy, F., & Murnane, R. J. (2003). The skill content of recent technological change: An empirical exploration. *The Quarterly Journal of Economics, 118*(4), 1279–1333.
Balsmeier, B., & Woerter, M. (2019). Is this time different? how digitalization influences job creation and destruction. *Research Policy, 48*(8), 103765.
Bolli, T., Breier, C., Renold, U., & Siegenthaler, M. (2015). *Für wen erhöhte sich das Risiko in der Schweiz, arbeitslos zu werden?* KOF Studien: Technical report.
Braun-Dubler, N., Langhart, M., & Gmünder, M. (2016). *ICT-Fachkräftesituation Bedarfsprognose 2024*. ICT-Berufsbildung Schweiz.
Bresnahan, T. F., Brynjolfsson, E., & Hitt, L. M. (2002). Information technology, workplace organization, and the demand for skilled labor: Firm-level evidence. *The Quarterly Journal of Economics, 117*(1), 339–376.
Cangemi, V., Capezzali, E., Chételat, M., Farine, A., Häfliger, J., & Rouvinez Mauron, A. (2015). Schweizerische lohnstrukturerhebung 2012. *BFS) BfS, editor. Neuchâtel*.
Caroli, E., & Van Reenen, J. (2001). Skill-biased organizational change? Evidence from a panel of british and french establishments. *The Quarterly Journal of Economics, 116*(4), 1449–1492.
David, H., & Dorn, D. (2013). The growth of low-skill service jobs and the polarization of the US labor market. *American Economic Review, 103*(5), 1553–97.
Deaton, A. (1985). Panel data from time series of cross-sections. *Journal of Econometrics, 30*(1–2), 109–126.
Falk, M., & Biagi, F. (2017). Relative demand for highly skilled workers and use of different ICT technologies. *Applied Economics, 49*(9), 903–914.
Frey, C. B., & Osborne, M. A. (2017). The future of employment: How susceptible are jobs to computerisation? *Technological Forecasting and Social Change, 114,* 254–280.
Goldin, C. D., & Katz, L. F. (2009). *The race between education and technology*. Harvard: Harvard University Press.
Goos, M., & Manning, A. (2007). Lousy and lovely jobs: The rising polarization of work in Britain. *The Review of Economics and Statistics, 89*(1), 118–133.
Goos, M., Manning, A., & Salomons, A. (2009). Job polarization in Europe. *The American Economic Review, 99*(2), 58–63.
Guillerm, M. (2017). Pseudo-panel methods and an example of application to household wealth data.
Hagsten, E., & Sabadash, A. (2017). A neglected input to production: The role of ict-schooled employees in firm performance. *International Journal of Manpower, 2,* 99.
Hansen, M. T., & Birkinshaw, J. (2007). The innovation value chain. *Harvard Business Review, 85*(6), 121.
Hanushek, E. A., Schwerdt, G., Woessmann, L., & Zhang, L. (2017). General education, vocational education, and labor-market outcomes over the lifecycle. *Journal of Human Resources, 52*(1), 48–87.
Hempell, T. (2003). Do computers call for training? Firm-level evidence on complementarities between ict and human capital investments.
Hoeckel, K., & Schwartz, R. (2010). Learning for jobs OECD reviews of vocational education and training. *Organisation for Economic Co-operation and Development (OECD), 2,* 666.
Hornstein, A., Krusell, P., & Violante, G. L. (2005). The effects of technical change on labor market inequalities. In *Handbook of economic growth*, volume 1 (pp. 1275–1370). Elsevier.
ILO (2012). International standard classification of occupations: Structure, group definitions and correspondence tables.
Kaiser, U. (2003). *Strategic complementarities between different types of ict-expenditures*. ZEW Discussion Papers: Technical report.
Katz, L. F. & Margo, R. A. (2014). Technical change and the relative demand for skilled labor: The United States in historical perspective. In *Human capital in history: The American record* (pp. 15–57). University of Chicago Press.
Katz, L. F., & Murphy, K. M. (1992). Changes in relative wages, 1963–1987: Supply and demand factors. *The Quarterly Journal of Economics, 107*(1), 35–78.
Krueger, D., & Kumar, K. B. (2004). Skill-specific rather than general education: A reason for US-Europe growth differences? *Journal of Economic Growth, 9*(2), 167–207.
Michaels, G., Natraj, A., & Van Reenen, J. (2014). Has ICT polarized skill demand? Evidence from eleven countries over twenty-five years. *Review of Economics and Statistics, 96*(1), 60–77.
Milgrom, P., & Roberts, J. (1990). The economics of modern manufacturing: Technology, strategy, and organization. *The American Economic Review, 3,* 511–528.
Milgrom, P., & Roberts, J. (1995). Complementarities and fit strategy, structure, and organizational change in manufacturing. *Journal of Accounting and Economics, 19*(2–3), 179–208.
Oesch, D., & Rodriguez Menes, J. (2011). Upgrading or polarization? Occupational change in Britain, Germany, Spain and Switzerland, 1990–2008. *Socio-Economic Review, 9*(3), 9999.
Rendall, M., & Weiss, F. J. (2016). Employment polarization and the role of the apprenticeship system. *European Economic Review, 82,* 166–186.
Roy, I., & Consoli, D. (2018). Employment polarization in Germany: Role of technology, trade and human capital. *The Indian Journal of Labour Economics, 61*(2), 251–279.
Schuler, M., Dessemontet, P., Joye, D., & Perlik, M. (2005). Die Raumgliederung der Schweiz.
SERI (2018). Vocational and professional education and training in switzerland–facts and figures 2018. In *Bern: State Secretariat for Education, Research and Innovation (SERI) Bern: State Secretariat for Education, Research and Innovation (SERI)*.
Stockinger, B. (2019). Broadband internet availability and establishments' employment growth in Germany: Evidence from instrumental variables estimations. *Journal for Labour Market Research, 53*(1), 7.
Swissuniversities (2015). Zulassung zum bachelorstudium an fachhochschulen. Best practices. *Bern: Swissuniversities)*.
Tambe, P., & Hitt, L. M. (2012). The productivity of information technology investments: New evidence from it labor data. *Information Systems Research, 23*(3), 599–617.
Taştan, H., & Gönel, F. (2020). Ict labor, software usage, and productivity: Firm-level evidence from turkey. *Journal of Productivity Analysis, 53*(2), 265–285.
Tsacoumis, S., & Willison, S. (2010). *O* NET analyst occupational skill ratings: Procedures*. Alexandria: Human Resources Research Organization.
Verbeek, M. & Nijman, T. (1992). Can cohort data be treated as genuine panel data? In *Panel data analysis* (pp. 9–23). Springer.
Wolter, S., Cattaneo, M., Denzler, S., Diem, A., Hof, S., Meier, M., & Oggenfuss, C. (2018). Swiss education report 2018. *SKBF/CSRE Swiss Coordination Centre for Research in Education*.

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