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ORIGINAL PAPER

The supply of foreign talent: how skill-biased technology drives the location choice and skills of new immigrants

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Abstract

An important goal of immigration policy is facilitating the entry of foreign-born workers whose skills are in short supply in destination labor markets. In recent decades, information and communication technology (ICT) has fueled the demand for highly educated workers at the expense of less-educated groups. Exploiting the fact that regions in Switzerland have been differentially exposed to ICT due to their pre-ICT industrial composition, we present evidence suggesting that more exposed regions experienced stronger ICT adoption, accompanied by considerably stronger growth in relative employment and wage premia for college-educated workers. Following this change in the landscape of relative economic opportunities, we find robust evidence that these regions experienced a much larger influx of highly educated immigrants in absolute terms as well as relative to lower educated groups. Our results suggest that immigrants' location decisions respond strongly to these long-run, technology-driven changes in their economic opportunities.

Keywords Immigrant sorting · International migration · Skill-biased technical change · Information and communication technology · Skill supply

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1 Introduction

International migrants in developed countries are increasingly highly educated. The number of immigrants with a tertiary degree heading to OECD countries grew by nearly 130% between 1990 and 2010 (OECD 2013). Foreign-born talent is unevenly distributed not only across destination countries, with four Anglo-Saxon countries (the USA, the UK, Canada, and Australia) accounting for nearly 70% of all high-skilled immigrants in 2010, but also across regions within destination countries (Kerr et al. 2016; Peri 2016). Understanding the driving forces behind the growth and unequal geographical distribution of foreign talent is important. Several studies highlight that high-skilled migrants contribute to growth and innovation (Peri et al. 2015; Kerr and Lincoln 2010; Beerli et al. 2021), facilitate international trade (Gould 1994; Head and Ries 1998), may have positive effects on public finances in host countries (Dustmann and Frattini 2014), and often benefit natives in the labor market (Beerli et al. 2021).[1] Consequently, policies facilitating the entry of foreign talent are popular among policymakers.[2]

Evidence from previous research based on cross-country data typically highlights that destination countries with higher earnings inequality attract larger shares of immigrants with a college degree (Grogger and Hanson 2011). Growth in earnings inequality has also been at the focus of a separate literature, reviewed by Acemoglu and Autor (2011) and Autor (2015), that documents the profound impact of information and communication technology (ICT) on the labor markets in OECD countries during the last 30 years. New automation technologies, which substitute for middle-skilled jobs and complement high-skilled ones, fueled the demand for talent and contributed to increasing earnings inequality. Little is known, however, about whether and how immigrants respond to these changing economic opportunities brought about by technological change. As promoting the entry of foreign talent is a commonly argued policy response to the growing inequality and "shortage of skills," it is crucial to understand how skill-biased changes in demand affect the flow, skill types, and location decision of immigrants.

In this paper, we provide comprehensive evidence that the local growth in foreign-born talent is a response to shifts in the local demand for skills driven by exposure to computerization. We focus on Switzerland, which is well-suited to study high-skilled immigration. From 1990 to 2010, the country experienced a considerable inflow of immigrants, increasing the share of foreign-born citizens from 20 to 29%. The share of new immigrants with a tertiary education grew from 17 to 44%, overtaking the

[1] However, some studies also find negative labor market impacts of high-skilled immigrants (Borjas and Doran 2015; Doran et al. 2016).

[2] In the USA, for instance, some politicians want to increase the selectiveness of its immigration policy by introducing a point-based system akin to the ones in Canada or Australia and abolish its current family-centered approach (Economist 2017).

share of natives (25% in 2010).[3] In 2002, Switzerland implemented a free movement policy (FMP), which abolished immigration restrictions for all EU citizens, but not for those from other parts of the world. This policy change allows us to study whether increased openness to immigration affected the skill supply of foreign workers. We exploit census data detailing the educational attainment of immigrants from an extensive set of origin countries settling in Swiss local labor markets from 1990 to 2010.[4] Our focus on local labor markets as destinations, where newly arriving immigrants settle, is motivated by testable predictions about the impact of ICT exposure on local economic opportunities. We augment these hypotheses with those from the literature on the location choice of immigrants with different skills. Together, this produces novel insights on the effects of ICT exposure on local economic opportunities and immigrants' response to them. We proceed in three steps.

First, we document the change in economic opportunities across local labor markets in Switzerland. We hypothesize that local labor markets are differentially exposed to computerization to the degree their industries were initially specialized in occupations with a high-routine task content. This hypothesis is inspired by the work of Autor and Dorn (2013), who document the impact of ICT on local labor markets in the USA more generally but not on newly arriving immigrants. The (testable) assumption is that ICT substitutes for workers with intermediate skills employed in routine-intensive occupations (e.g., clerks, assembly line workers, and machine operators) and complements highly educated workers in occupations with a high degree of abstract tasks, such as managers, professionals, and technicians. Falling ICT costs induce firms to substitute routine-intensive employment for computer capital and to hire workers complementary to ICT. We exploit that a region's industry mix in 1970 strongly determines its specialization in routine employment in later decades. This allows us to use a region's industry specialization in 1970 as an instrument for its routine specialization during our sample period. Paralleling the US experience, we find that local labor markets with higher initial routine specialization experienced stronger ICT investment and adoption, stronger employment growth at the top of the wage distribution, and a larger reduction of employment in intermediate wage ranks. Furthermore, we find evidence for a considerable increase in the wage gap between college and middle-educated workers in these regions. A novel result is that, in contrast to evidence for the USA, we find no indication of stronger employment growth at the bottom of the skill distribution due to ICT, in so-called manual or low-skilled service jobs. The ICT-induced growth of low-skilled service jobs, therefore, may be seen as less robust to changes in context. Similarly, the wage gap between middle-educated and lower educated workers did not change differentially across regions. We interpret these findings as suggestive evidence that progress in ICT fueled the demand for high-skilled workers in Swiss regions and, thus, increased the economic opportunities for them (relative to those with intermediate skills).

[3] Meanwhile, the share of middle educated remained constant at 26%, while the share of low educated decreased strongly from 57 to 29% (cf. table C3).

[4] A note on terminology. We define commuting zones (CZs) as local labor markets and use both interchangeably. We refer to skills as different levels of education unless otherwise specified.

Second, the main result of this paper is that the changes in economic opportunities due to ICT exposure had a strong impact on the skill mix of newly arriving immigrants. Our empirical analysis is guided by a simple location choice model (e.g., Grogger and Hanson 2011). Consistent with the prediction from this framework, we find that regions with higher routine specialization, and hence a larger increase in economic opportunities for talented workers, experienced a considerably stronger inflow of highly educated immigrants while the inflow of middle-educated immigrants was weaker in both decades between 1990 and 2010. Our preferred specification suggests that, on average, a 5 percentage point higher local routine specialization (roughly equal to the cross-region interquartile range) led to a 14% higher inflow of tertiary educated immigrants relative to those with middle education. At the lower end of the skill spectrum, we find no evidence for a differential inflow of immigrants with intermediate relative to lower skills. This is consistent with the insignificant change in the relative economic opportunities of the lower two skill groups. The change in the education mix of immigrants is paralleled by a change in their occupational composition: while the typical, newly arriving immigrant in 1990 was working in a lower qualified occupation such as craft, elementary, and service occupations, ICT exposed regions attracted more new immigrants working as professionals, managers and technicians and fewer working in middle-skilled craft occupations. We explore numerous alternative explanations for the differential inflow of highly and moderately skilled immigrants including the regional importance of ethnic networks, agglomeration effects, offshoring, and manufacturing decline. None of these factors nor a comprehensive set of sensitivity analyses invalidates these findings. Investigating the heterogeneity of these effects across sectors and regions, we find a much more pronounced inflow of highly educated immigrants into the service sector compared to manufacturing.

Third, we analyze whether and how the inflow and location decisions of immigrants with different education levels changed when immigration restrictions were significantly altered. We exploit that Switzerland adopted a free movement policy in 2002, which liberalized access to the Swiss labor market for workers from EU member states. Immigration from other countries continued to be subject to quotas and restrictions. Using a difference-in-differences strategy, we find that the FMP strongly increased the inflow of EU relative to non-EU immigrants in all education groups. We cannot reject the hypothesis, however, that the policy only affected the total inflow of immigrants but not the relative supply by skill group.

Taken together, our results suggest that exposure to skill-biased technology led to strong shifts in the relative demand for highly educated versus middle-educated workers, changing their relative economic opportunities. The change in the landscape of relative economic opportunities attracted the supply of foreign talent (in absolute as well as relative terms). The last part of our analysis suggests that the abolishment of immigration restrictions did not alter this response.

This paper makes important advances to a number of literatures. First, it relates to a growing literature on the determinants of talent flows and immigrant sorting across destination countries and regions (see, inter alia, Beine et al. 2016; Parey et al. 2017). While the growth in highly skilled migration and their clustering in

Anglo-Saxon countries or across regions in the USA has been highlighted previously (Peri 2016; Kerr 2019), we know relatively little about factors driving these patterns across time and space. An exception is Grogger and Hanson (2011), who show that countries with higher earnings inequality attract a higher share of tertiary educated immigrants, a phenomenon referred to as *positive sorting*. We extend this analysis in at least four ways. First, we find evidence for positive sorting already in 1990 in different regions *within* Switzerland as one destination country. Second, an important novel finding is that *positive sorting accelerated considerably between 1990 and 2010*. This is consistent with the increase in the number and clustering of immigrant talent across countries documented globally. Third, to the best of our knowledge, this is the first paper extending prior work by highlighting the central role of ICT as one specific *cause* for these trends. Fourth, by exploiting a plausibly exogenous shock to a full range of relative economic opportunities, we offer an alternative to the common approach in the literature studying immigrant sorting, which typically correlates immigrant flows with potentially endogenous earnings differentials.[5] This is advantageous since earnings differentials might only capture part of the relative differences in economic opportunities, as pointed out by Amior and Manning (2018, p1942), that foreign-born workers factor into their immigration decision (next to employment opportunities created). In short, our findings show that Gould and Moav's (2016, p. 1090) observation that economic inequality "determine[s] how a country competes internationally to attract high skill immigrants" extends even to the sub-national local labor market level.

Second, our paper relates to a larger literature documenting the impact of ICT on local labor markets within countries.[6] This literature highlighted several adjustment mechanisms, e.g., the within-country reallocation of high-skilled workers across differentially exposed regions and of low-skilled workers across occupations (Autor and Dorn 2013; Autor et al. 2015), and the predominant role of young workers in the growth of high-skilled employment (Autor and Dorn 2009). In this paper, we highlight the entry and endogenous location decision of newly arriving immigrants as one important, and previously undocumented, local adjustment mechanism to the impact of ICT. Larger entry of foreign-born talent is one way local supply of skills may increase. This channel is complementary and potentially faster than the endogenous skill supply through youth's investment in higher education. Concurrently developed as our paper, Mandelman and Zlate (2022) and Basso et al. (2020) show for the USA that the ICT-induced growth in low-skilled service sector jobs at the bottom of the wage distribution documented by Autor and Dorn (2013) is mainly driven by low-skilled foreign workers. Our findings illustrate that the absorption of foreign workers into low-skilled service jobs is possibly specific to context. For the Swiss context, we show that the absence of a strong differential response of middle-to-low-educated

[5] An exception is Wilson (2020) who studies the migration response to fracking.

[6] After Autor et al.'s (2003) seminal contribution introducing the task framework to evaluate the impact of ICT in the US labor market, its impact have also been studied in the UK (Goos and Manning 2007), Europe (Goos et al. 2014), Germany (Dustmann et al. 2009; Spitz-Oener 2006), and across countries (Michaels et al. 2014).

immigrants can be rationalized by the fact that economic opportunities did not change differentially in the lower half of the wage distribution. We do find, however, a strong response of highly educated immigrants adopting work in high-paying occupations, which was more modest in the USA.

Finally, our study contributes to the literature evaluating the effect of immigration policies on the inflow of immigrants and their impact on the local economy. Earlier studies pointed to a complementarity between weaker immigration restrictions and greater demand-pull forces in destination countries leading to larger total inflows of immigrants (McKenzie et al. 2014; Mayda 2010; Ortega and Peri 2013). One example from our context is Beerli et al. (2021) who find that the abolishment of immigration restrictions for EU workers in Switzerland after 2002 led to a strong inflow of mostly highly educated immigrants and benefitted firms in skill-intensive sectors and those expressing difficulties to recruit skilled workers prior to the reform.[7] Our paper's results highlight that a strong, long-term, and technology-induced increase in the demand for skills is the underlying cause that led to relatively stronger inflows of highly educated immigrants. This trend in the skill mix was already present before the reform. However, the reform accentuated the inflows of immigrants in all education groups and might have allowed regions with the largest skill demand to attract even more talent.

The remainder of this study proceeds as follows. In Section 2, we lay out the conceptual framework and empirical strategy of our main specifications. In Section 3, we describe the data and variable construction we use, the context of immigration policies, and present descriptive statistics. In Section 4, we discuss our main results: the impact of ICT exposure on economic opportunities, the response in the skill mix of immigrants, and to what degree the free movement policy affected this response. Section 5 concludes our paper. All referenced supplementary material (including tables and figures denoted with alphabetic letters) can be found in Beerli et al. (2021).

2 Conceptual framework and empirical strategy

2.1 Modeling immigrant sorting

We are interested in how newly arriving immigrants sort into local labor markets based on ICT-induced changes in economic opportunities. To fix ideas, we specify a simple but general gravity model with linear utility analogous to Grogger and Hanson (2011).[8] We adapt their sorting equation with two education groups to our context

[7]Beerli et al. (2021) exploit that the reform led to a stronger inflow of cross-border workers in regions close to the Swiss border. While we focus on newly arriving resident immigrants in this paper, we provide suggestive evidence that the skill mix of cross-border workers responded in a similar way to ICT exposure (see table C7). In addition, we also show that the influx of cross-border workers in regions close to the border did not alter the response of newly arriving resident immigrants there (in table C6).

[8]For a recent review, see Beine et al. (2016) that discusses the motivation and microeconomic foundation of gravity models in migration research more generally.

with three education groups. This allows capturing potentially non-monotone effects along the skill distribution.

In this model (c.f. Grogger and Hanson 2011, equation 6), immigrant sorting can be written as

$$\ln \frac{N_{rst}^{j}}{N_{rst}^{j-1}} = \alpha^{j}(v_{rt}^{j} - v_{rt}^{j-1}) - \alpha^{j}(g_{rst}^{j} - g_{rst}^{j-1}) + (q_{st}^{j} - q_{st}^{j-1}) \tag{1}$$

where the (log) number of individuals with education level j (relative to those with education $j-1$), $\ln \frac{N_{rst}^{j}}{N_{rst}^{j-1}}$, migrating from source country s to destination region r in year t is a function of three education-specific difference vectors: (i) destination characteristics (pull factors), $v_{rt}^{j} - v_{rt}^{j-1}$, such as education-specific wages, employment possibilities, or the region's general amenities, (ii) source country characteristics (push factors), $q_{st}^{j} - q_{st}^{j-1}$, such as wages, political stability, and supply of skills, (iii) destination-by-source characteristics, $g_{rst}^{j} - g_{rst}^{j-1}$, most commonly considered the pecuniary and non-pecuniary costs of migrating from r to s, such as source country and skill-specific immigration restrictions or psychological costs of moving.[9]

To study the long-run impact of destination regions' potential exposure to ICT adoption, we take the first difference across decades of Eq. (1). This cancels factors common to both education groups that do not change across decades, e.g., local amenities, bilateral geographic distances, or language. Then, the *change* in the relative number of immigrants by education group is a function of *education-specific changes* in push and pull factors as well as changes in bilateral migration costs. The coefficient vector α^{j} governs the impact of these factors.[10] For instance, setting $j = 3$, an ICT-induced rise in the wage premium for high relative to middle education, i.e., $w_{rt}^{3} - w_{rt}^{2}$, would, ceteris paribus, lead to an increase in the number of highly relative to middle-educated immigrants, i.e., $\alpha_{wage}^{3} = \frac{\partial \ln \frac{N_{rst}^{3}}{N_{rst}^{2}}}{\partial (w_{rt}^{3} - w_{rt}^{2})} > 0$.

2.2 Exposure to ICT

Our main interest lies in estimating the effect of changing economic opportunities in destinations $(v_{rt}^{j} - v_{rt}^{j-1}) - (v_{rt-1}^{j} - v_{rt-1}^{j-1})$ on the change in the skill mix of immigrants, $\ln \frac{N_{rst}^{j}}{N_{rst}^{j-1}} - \ln \frac{N_{rst-1}^{j}}{N_{rst-1}^{j-1}}$. The standard approach in the literature is to estimate

[9]In the structural model of Grogger and Hanson (2011), immigrant sorting depends only on education-specific wages in the destination and source countries, education-specific migration costs, and the skill supply in the source country. In their case, the pull vector, $v_{rt}^{j} - v_{rt}^{j-1}$, includes only wages and the push vector, $q_{st}^{j} - q_{st}^{j-1}$, corresponds the sum of skill supply and wages in the source country, i.e., $\ln(N_{st}^{j}/N_{st}^{j-1}) - \alpha^{j}(v_{st}^{j} - v_{st}^{j-1})$. In our Eq. (1), the push and pull vectors include a more general representation of economic opportunities including wages and also employment possibilities. We will see in Section 4.1 that wage changes capture only part of ICT-induced changes in economic opportunities for immigrants.

[10]Note that in the estimation, we allow the parameters to be different for push and pull factors and for bilateral migration costs.

Eq. (1) using differences in income levels between education groups, both in destinations and origin countries and proxies or high-dimensional fixed effects to absorb bilateral migration costs (see, e.g., Bertoli and Fernández-Huertas Moraga 2013). In contrast, we exploit the exposure to ICT as a plausibly exogenous and skill-biased demand shock in Swiss local labor markets. By focusing on labor markets within a country, this approach eliminates several potential confounders associated with location choice of a more diverse set of destinations as in a cross-country comparison.

Based on testable predictions from a large body of literature on ICT and job polarization, we hypothesize that ICT affected economic opportunities in Swiss local labor markets differently to the degree they were differentially specialized in routine task-intensive jobs in the pre-ICT era.[11] The idea is that ICT *substitutes* for workers employed in occupations with a high content of routine manual or routine cognitive tasks, such as assembly line workers or bank clerks, respectively, which typically had intermediate wage levels. On the other hand, ICT *complements* workers in managerial or professional occupations, typically entrusted with non-routine, abstract, creative, or problem-solving tasks at the top of the wage distribution. Relative to rather slow progress in the 1960s and 1970s, computing prices fell more rapidly after 1980 which continued well until the mid-2000s and made microprocessors widely available (Nordhaus 2007). This provided strong incentives for firms to substitute ICT for routine workers, driving down their wages and employment opportunities. In contrast, it increased the demand for workers in abstract occupations leading to wage and employment gains for them.

Autor and Dorn (2013) provide evidence that these predictions have *geographical impact*: local labor markets in the USA with a larger historical specialization in routine employment experience larger wage and employment growth in high-paying and low-paying occupations relative to those with intermediate pay. Thus, these regions experience the typical wage and employment polarization. In addition, Michaels et al. (2014) show that ICT affected workers with different education levels differently. Since middle-educated workers were more likely to work in routine occupations and college-educated workers worked more in abstract occupations, ICT lowered employment and wages for the first group and increased it for the latter. For lower educated workers, the effect was ambiguous since they worked in occupations intensive in routine and non-routine manual tasks.

We measure a local labor market's potential exposure to the impact of ICT by the degree it was historically specialized in routine task-intensive occupations. To allow comparisons with international evidence, we closely follow Autor and Dorn (2013) in the construction of this measure. We proceed in two steps. First, we merge measures of an occupation's intensity in three tasks (routine, manual, abstract) available in the US Department of Labor's (1977) Dictionary of Occupational Titles (DOT) with

[11] The idea of routine intensity as a proxy for relative demand shifts affecting the wage differential of workers with different educational backgrounds or skills has found wide application in the literature on skill-biased technical change and job polarization. See Acemoglu and Autor (2011) for an overview of the relevant literature.

occupations in the Swiss Census data.[12] We combine the task measures from the DOT to create a measure of routine intensity by occupation,

$$RTI_{kt_0} = \ln\left(T^R_{k,t_0}\right) - \ln\left(T^M_{k,t_0}\right) - \ln\left(T^A_{k,t_0}\right) \tag{2}$$

where T^R_{k,t_0}, T^M_{k,t_0}, and T^A_{k,t_0} denote an occupation k's intensity in routine, manual, and abstract tasks in the base period t_0, here 1980. Each task is measured on a 0 to 10 scale, with ten meaning that the task is most heavily used in this occupation. A limitation of these DOT variables is that they do not have a cardinal scale. Akin to the literature, we transform the RTI measure into percentile values corresponding to the percentile rank in the 1980 distribution of the RTI measure across occupations. Therefore, the constructed index, RTI_{k,t_0}, rises if routine tasks are used more intensively in an occupation and falls with the use of manual and abstract tasks.

Second, we classify occupations as routine-intensive if they fall into the top-third of the employment weighted distribution of the RTI measure.[13] Then, we calculate for each local labor market the employment share in routine-intensive occupations as

$$RSH_{rt} = \left(\sum_{k=1}^{K} L_{rkt} \times 1[RTI_{k,t_0} > RTI^{P66}_{t_0}]\right)\left(\sum_{k=1}^{K} L_{rkt}\right)^{-1} \tag{3}$$

where L_{rkt} is the employment in occupation k in region r and decade t. 1[.] indicates that an occupation k is routine intensive as defined above.

Taken together, the prediction from the literature is that local labor markets with a larger initial share of routine employment, as measured above, experience a larger positive demand shift for high relative to middle-educated workers, while the demand shift between middle and low is ambiguous:

$$\frac{\partial[(v^3_{rt} - v^2_{rt}) - (v^3_{rt-1} - v^2_{rt-1})]}{\partial RSH_{rt}} > 0 \quad \text{and}$$

$$\frac{\partial[(v^2_{rt} - v^1_{rt}) - (v^2_{rt-1} - v^1_{rt-1})]}{\partial RSH_{rt}} \lesseqgtr 0.$$

2.3 Empirical strategy and identification

To test these predictions, we estimating the following reduced form equation

$$\ln\frac{N^j_{rst}}{N^{j-1}_{rst}} - \ln\frac{N^j_{rst-1}}{N^{j-1}_{rst-1}} = \tau^j RSH_{rt-1} + x'_{rst-1}\gamma^j + \delta^j_{st-1} + \delta^j_c + \varepsilon^j_{rst-1}, \tag{4}$$

where we estimate separate models for (i) highly educated relative to middle-educated immigrants, and (ii) middle-educated relative to low-educated immigrants.

[12] See more details on task measures and construction of routine share in appendix A.

[13] The choice of the 66 percentile and the log aggregation are ad hoc but have been implemented in several contexts and shown to be robust to using alternatives cutoffs (Autor and Dorn 2013).

Thus, all the estimated parameters are allowed to be j-specific. The key parameter of interest, τ^j, measures the degree to which Swiss local labor markets with higher specialization in routine employment experience larger growth in the number of individuals with a higher education level (j) relative to those with a lower education level ($j-1$). Given suggestive evidence on how ICT exposure impacts relative economic opportunities in Section 4.1, we conjecture that it affects the relative inflow of high-to-middle-educated immigrants positively ($\tau^3 > 0$) and has an ambiguous effect on the relative inflow of middle-to-low-educated immigrants ($\tau^2 \lesseqgtr 0$).

We include a full set of source-by-decade fixed effects, δ^j_{st}, to absorb any variation from source country-specific push factors by decade. This is important as we stack the two sets of first-differences, 1990–2000 and 2000–2010, in our baseline regression although we also explore estimates separately by decade (cf. Autor and Dorn 2013; Autor et al. 2013). Furthermore, we include fixed effects for cantons, δ^j_c, the Swiss equivalent to the US state with commuting zones as a nested geographical subunit. This allows absorbing regional trends in attractiveness associated with, for example, institutional or cultural differences across regions.[14] Conditioning on Canton fixed effects implies that the identifying variation of our ICT exposure comes from a cross-sectional within-Canton variation of RSH_{rt}. Finally, we assess the importance of local area characteristics, origin country characteristics, and their interactions in x_{rst-1}, e.g., the pre-existing share of immigrants from s in r, which accounts for variation in bilateral migration costs. For all of these variables we use beginning of period values. ε^j_{rst-1} denotes an error term.

This approach has two advantages compared to using local wage differentials by education as measures for a region's economic opportunities. First, wage differentials may be endogenous to immigration.[15] Second, demand-induced changes in economic opportunities might only partly be reflected in wage changes due to wage rigidities or institutional constraints (see Cadena and Kovak 2016 for a similar argument). We overcome both issues by exploiting the exposure to ICT as a plausibly exogenous shift to local skill demand and, thus, a shift in skill-related economic opportunities (reflected in both wages and employment).

We use an instrumental variable strategy that extracts the long-run, quasi-fixed component of the routine employment share akin to Autor and Dorn (2013) or Autor et al. (2013). The basic idea is to exploit only variation in local routine task specialization that is due to a region's industry specialization determined *prior* to the strong advancement in computerization after 1980. This also allows circumventing the potential reverse causality concerns that the inflow of highly educated immigrants could spur technological change as in Lewis (2011). Thus, we use the industry com-

[14] Appendix figure C1 illustrates the spatial distribution of the routine share in Swiss commuting zones across decades. Table C1 shows that the within-Canton variation in the routine share is usually larger than the between-Canton variation.

[15] For our analysis period, Beerli et al. (2021) provide evidence that abolishment of immigration restrictions with the Free Movement of Persons treaty after 2002 between Switzerland and the EU increased wages of highly educated native workers but not of lower educated natives in regions close to the Swiss border.

position of regions in the first available Swiss census in 1970 as an instrument for the observed routine share in later decades:

$$\widetilde{RSH}_{r1970} = \sum_i \frac{L_{ir1970}}{L_{r1970}} \times RSH_{i-r1970}, \tag{5}$$

where $\frac{L_{ir1970}}{L_{r1970}}$ is an industry i's employment share in total employment in region r in 1970. $RSH_{i-r1970}$ is an industry i's share of workers employed in routine occupations, averaged across all regions in 1970 except region r. The product of these two measures gives the predicted value of a commuting zone's share in industry employment which is based on its industry mix in 1970 and an industry's typical share of workers in routine occupations nationally.[16]

This approach has been used extensively in the literature, and its relevance and validity were established in various contexts.[17] In the Swiss case, the relevance is very high, confirming the usefulness of the approach in our setting and data. Table C2 shows that a region's industry composition in 1970 is a strong predictor of its routine employment share both in 1990 and in 2000 as well as when we stack both decades. The F-statistics are well beyond conventional rules of thumb. For each percentage point increase in the historical share, the contemporaneous share rises by approximately half a percentage point. Moreover, the historical routine share can explain roughly 70% of the geographical variation in the contemporaneous routine share (as indicated by the R^2s).

The validity of this instrumental variable strategy hinges on the untestable assumptions (i) that conditional on covariates (and fixed effects), the initial routine specialization in 1970 only affects the differential inflow of immigrants by education through its effect on a commuting zone's beginning of period routine specialization, and (ii) the causality does not run the other way around, i.e., from immigrant inflows to the initial routine specialization. In this respect, the static nature of this instrumental variable approach has, akin to a large literature on job polarization, advantages and disadvantages that should be kept in mind when interpreting the results. On the one hand, exploiting the pre-determined industry specialization in 1970 allows for a clean extraction of the long-run component in routine specialization and addresses potential concerns about reverse causality. The 1970 industry composition captures much of the conditional variation in routine specialization in later decades, evident in the strong first stage and the similarity between OLS and 2SLS estimates shown below (see Table 3). On the other hand, exploiting the pre-determined industry specialization prevents including fixed effects at lower levels, e.g., at the CZ level.

[16] One potential concern about the construction of both the local routine share, RSH_{rt}, and of its instrument, $\widetilde{RSH}_{r1970}$, is that we use total employment including immigrants. If the employment of previous immigrants was highly concentrated in routine-intensive jobs, higher routine shares could be correlated with stronger ethnic networks with previous immigrants as in Card (2001). We directly test the robustness of our main estimates by controlling for ethnic networks in Table 4 and also show robustness when the routine share, and its instrument, is constructed with native employment only in table C8.

[17] Examples of countries in which the approach has been applied include, among others, Germany (Rendall and Weiss 2016; Borrs and Knauth 2021), the USA (Lordan and Neumark 2018; Zhang 2019), the UK (Montresor 2019), and several EU countries (Blanas et al. 2019).

In Section 4.3, we provide several pieces of evidence corroborating the validity of this approach. First, we show that routine specialization is not spuriously correlated with other factors that could affect the inflow of immigrants with different education levels. Including such other factors, x_{rst-1}, into our specification changes the effect of our main regressor little. Similarly, we get qualitatively similar results when we use different samples, only use native employment to construct the routine share variables or collapse our data at the level of municipalities and include CZ fixed effects that absorb CZ-trends. Most notably, we show that there are no pre-trends in differential inflows of immigrants by education: in the 1970s, i.e., the decade prior to rapid computerization, regions with different degrees of initial routine specialization experienced essentially similar inflow from immigrants with different education levels.[18]

A final point, related to the interpretation of the RSH measure, is whether it is a good proxy for the extent to which the falling price of ICT after 1980 induced firms to computerize routine tasks and, thereby, replace workers previously entrusted with these tasks. In appendix A.2 we provide suggestive evidence corroborating the interpretation of a commuting zone's initial routine specialization as exposure to computerization between 1990 and 2010 for the Swiss context. Exploiting auxiliary data from the KOF Innovation Survey, a representative survey of Swiss establishments, we show that a higher initial routine specialization is associated with (i) a higher increase in the share of computer users inside firms, and (ii) a higher growth in the share of investment going to ICT technology (both software and hardware). Using data from the Swiss Census, we provide additional evidence that higher initial routine specialization is correlated with (iii) larger growth in the share of workers employed as computer professionals, and (iv) stronger declines in the share of workers employed as clerks, machine operators and craft workers generally considered as routine-intensive occupations.[19]

3 Data, institutions, and descriptive statistics

3.1 Data sources

Our main data source is the Swiss Census in 1990 and 2000, covering the full resident population and in its successor the Structural Surveys. The latter is a yearly micro-census from which we pool the years 2010 to 2012 to gain accuracy. We

[18] One question is whether immigrants make dynamic, forward-looking settling decisions and take into account future relocations within Switzerland at the time of arrival. To address these decisions empirically, we would require a structural approach (Buchinsky et al. 2014; Gallin 2004) and longitudinal information which is not included in the census data. We believe that such forward-looking considerations are less relevant in our context for the following reasons: (1) on-ward migration of immigrants in Switzerland is quite small even on the municipality level (approximately 6–11% in 2000, see Liebig et al. 2007), (2) our baseline sample considers commuting zones as destinations for which this concern is probably even smaller, (3) effects from (directly) neighboring regions are absorbed by canton fixed effects.

[19] See appendix A.2 for details on data and variables related to computerization.

classify individuals as *new immigrants* (we will use new and recent immigrants interchangeably hereafter), if they were born abroad, arrived in Switzerland less than 5 years prior, and resided in Switzerland in the census year. We focus on these resident immigrants since they represent the typical “international migrant” discussed in the literature (e.g., Grogger and Hanson 2011) and are most affected by the change in economic opportunities discussed in this paper.[20]

Among new immigrants, the census allows distinguishing 33 different *origin countries* based on the country of residence 5 years prior to the census.[21] We classify individuals into three education groups using the International Standard Classification of Education (ISCED) as in Dustmann et al. (2009). *Highly educated* individuals hold a tertiary degree (ISCED 5 and 6), whereas *middle-educated* individuals hold a degree from a secondary school (ISCED 3 and 4). *Low-educated* individuals are those with compulsory education only or less (ISCED 0, 1 and 2). As *destinations*, we use the 106 Swiss commuting zones (CZs) defined by the Federal Statistical Office (Schuler et al. 2005). CZs are constructed to represent local labor markets such that the majority of people commute to work within its boundaries.

Our base sample consists of the *population* of new immigrants, older than 15 years of age with non-missing information in education and place of residence (when we focus on workers, we use those aged 18–64). We then aggregate these into year, CZ, origin country, and education group cells and deal with the presence of zero or missing bilateral migration stocks by adding one to all cells. This is done to prevent sample selection due to zero-migration flows (when using log numbers) and to keep a consistent sample throughout. This procedure is robust to several alternative adjustments.[22] Differencing across decades leaves us with a sample of 6,996 observations (2 decades $\times$ 33 origin countries $\times$ 106 CZs) for each education group.

In Section 4.1, we use additional datasets to measure the impact of ICT on economic opportunities by skill type in Swiss local labor markets. First, we use the Swiss Earnings Structure Survey (SESS) to illustrate the effect of ICT on mean

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[20] Note that this definition does not include cross-border workers. The latter group of foreign-born workers resides in one of the neighboring countries (Germany, Italy, France, Austria) and commutes to work in the Swiss border region daily. Thus, they are not included in the Census residency population. Their labor supply is very concentrated close to the Swiss border and negligible farther away (Beerli et al. 2021). For these reasons, cross-border workers face a quite different set of incentives affecting their decision of where to work compared to typical resident immigrants discussed in the literature. We find similar effects of ICT exposure on this group’s education levels but abstract from them in the analysis for data consistency reasons.

[21] See additional details on the construction of the origin country information in appendix A. One origin country category subsumes missing origin information. We present robustness to dropping this category from the sample in table C8.

[22] Bilateral stocks should be positive in expectation (cf. arguments in Ortega and Peri 2013), though some might be zero in finite populations. To assess the sensitivity of our results based on the log transformation (Silva and Tenreyro 2006), we do a number of different robustness checks. First, we use the hyperbolic sine transformation instead of the $log(x + 1)$ transformation which gives almost identical results (table C8). Second, in a previous version of this paper, Beerli and Indergand (2016) provide evidence that the routine share has a qualitatively similar effect on education group shares of immigrants. The latter outcome measure is not affected by the zero cells problem.

hourly wages by education group. The SESS collects labor market and demographic information of individuals employed in a representative sample of private sector companies biannually between 1994 and 2010. We restrict the sample to all employees (natives and immigrants) with non-missing information regarding wages, hours worked, place of work, and basic demographic variables.[23] We complement this data with the Swiss Labor Force Survey (SLFS) that allows measuring wages at the level of detailed ISCO occupations. Using the same sample restriction as for the SESS, we compute the average log hourly wage for each ISCO occupation to measure skill rank in the pooled SLFS sample covering 1991–1993, as explained in more detail below. Finally, to assess the firm-level investment in ICT we rely on the KOF Innovation Survey, which we discuss in more detail in Appendix A.2.

To analyze the impact of the FMP policy in Section 4.5, we replace the source-by-decade fixed effects with a rich set of controls for time-varying origin country push factors described in more detail in Appendix A. In particular, we include proxies for the change in skill supply in origin countries, proxies for wage differences between education groups in origin countries, and a set of additional origin-by-decade controls.

3.2 Immigration policy context

Before 2002, people from all origin countries who wanted to work and reside in Switzerland had to apply for a resident permit.[24] Permits were subject to global yearly quotas set by the federal government and distributed to Cantons proportionally based on population size. Cantonal immigration offices granted permits conditional on employment and only if no equally qualified native could be found for a given job vacancy.[25] Immigrants from EU17 and EFTA countries were granted priority in awarding permits relative to immigrants from other countries (e.g., those from the USA or Canada). The implementation of the EU's free movement of persons (FMP) principle after 2002 gradually liberalized access for EU workers to the Swiss labor market. Residency in Switzerland remained conditional on employment but restrictions on employment were gradually and, later, fully abolished. For immigrants from non-European origin countries, all restrictions remained similar to those in the 1990s. Thus, this policy change affected immigrants from different origins differently but was implemented nationwide (and hence did not differ across regions) and did not include targeting certain skills. We interpret the implementation of the FMP as an exogenous change to migration restrictions. In fact, accepting the FMP policy as one

[23] We drop individuals with real hourly wages below the 1st and above the 99th percentile of the wage distribution each year to avoid effects from outliers.

[24] Here, we focus on immigration policies from 1990 to 2010. Appendix B provides further details on immigration policies and Kunz (2016) reviews the migration history prior to the sample period.

[25] Firms needed to provide details about working conditions and job requirements to Cantonal migration offices prior to hiring immigrants. They needed to demonstrate that a search for suitable native workers was unsuccessful. Migration offices, in turn, checked whether equally qualified native workers were registered as unemployed. This procedure imposed particular administrative hurdles and costs for hiring immigrants.

of the EU's central pillars, was a necessary concession made to Switzerland to pass a larger package of bilateral agreements.[26]

In table C3 we show the number of new immigrants by origin country group (EU and non-EU) and education level.[27] In 1990, roughly 60% of all new immigrants arrived from European countries (old and new member states). Between 1990 and 2010, the number of new arrivals from the EU increased considerably, while the corresponding number from non-EU countries decreased slightly. Thus, by 2010, immigrants from EU countries constituted 80% of all new arrivals. In contrast to the absolute numbers, the change in the skill mix of EU and non-EU countries was remarkably similar. Both origin groups experienced a strong decrease in the share of low educated and a strong increase in the share of highly educated individuals. The share of middle-educated remained roughly constant in both groups. Although the levels are different, the changes in high-to-middle-educated shares are very similar, suggesting a similar response to local pull factors, irrespective of the origin country.

It is a natural question to ask to which degree the changes in education levels among immigrants simply resemble those in their origins? In our baseline specification, we cannot answer this question as gains in educational attainment in origin countries are fully absorbed through source-by-decade fixed effects. Table C4 provides further insights on this by showing average education levels, separately for EU and Non-EU countries. First, immigrants were *positively selected* already in 1990 paralleling the observation by Grogger and Hanson (2011). Second, immigrants became *more positively selected* between 1990 and 2010. While the share of low educated fell almost equally among immigrants as in the origin countries, the share with a college education grew three to four times faster among immigrants than in their origins. In contrast, the share of the middle educated stagnated among immigrants and grew strongly in origin countries. This suggests that gain in educational achievement in origin countries did not *mechanically* change education among new immigrants.

3.3 Characteristics of local labor markets and task-based specialization of education groups

To understand the endogenous immigration responses due to computerization, we analyze immigration into Swiss commuting zones (CZs) with different levels of exposure to ICT. Table 1 presents descriptive summary statistics, separately for CZs above and below the regional median routine share in 1970, i.e., $\widetilde{RSH}_{j,1970}$ (as defined by Eq. (5)). A few facts are noteworthy. First, high-routine CZs represent a larger share of total Swiss employment throughout all years. Second, these regions have different industrial compositions. A lower share of their workforce is employed in agriculture/mining and construction/utilities while they are relatively more intensive

[26] The FMP policy's limited popularity was a major reason why the entire bilateral package had to go through a national referendum vote in May 2000, in which it was approved, and, yet, the Swiss population voted in favor of reintroducing immigration restrictions in February 2014.

[27] Table C11 provides summary statistics for the full list of origin countries in our sample.

Table 1 Characteristics of high and low routine regions 1990–2010

	CZs above median $\widetilde{RSH}_{r1970}$			CZs below median $\widetilde{RSH}_{r1970}$		
	Level	Changes		Level	Changes	
	1990	1990–2000	2000–2010	1990	1990–2000	2000–2010
# total employment	2,033,934	− 219,023	537,657	675,576	− 11,252	260,756
Share high-routine occupations (%)	0.34	− 0.02	− 0.03	0.30	− 0.01	− 0.02
Industry shares						
Agriculture/fishing/mining (%)	0.03	0.00	− 0.00	0.08	− 0.01	− 0.03
High-tech manufacturing (%)	0.10	− 0.02	− 0.01	0.08	− 0.01	− 0.01
Low-tech manufacturing (%)	0.10	− 0.02	− 0.02	0.12	− 0.02	− 0.02
Construction/utilities (%)	0.09	− 0.02	0.00	0.11	− 0.02	0.00
Knowledge-intensive services (%)	0.34	0.08	0.03	0.26	0.06	0.04
Less knowl.-intens. services (%)	0.34	− 0.02	− 0.00	0.34	− 0.00	0.00
Wage structure (in CHF)						
Hourly wage highly educated	55.88	0.55	1.68	48.07	0.78	1.48
Hourly wage middle educated	35.58	0.46	0.05	31.68	0.83	0.75
Hourly wage low educated	27.43	0.33	0.28	25.67	0.48	1.33
Wage difference high vs middle	20.30	0.09	1.63	16.39	− 0.05	0.73
Wage difference middle vs low	8.15	0.13	− 0.23	6.01	0.35	− 0.58
New immigrants						
# new immigrants	180,300	− 39,275	230,289	53,612	− 20,049	63,391
Share highly educated (%)	0.18	0.22	0.07	0.12	0.16	0.05
Share middle educated (%)	0.26	− 0.02	0.01	0.27	− 0.00	0.05
Share low educated (%)	0.56	− 0.20	− 0.08	0.61	− 0.15	− 0.10

Notes: This table shows levels of descriptive statistics in 1990 and their changes (1990–2000, 2000–2010), separately for commuting zones above and below the median of their historical routine share $\widetilde{RSH}_{r1970}$. Apart from the wage measures, data are from the Swiss Census 1970, 1990, 2000 and the Structural Surveys 2010–2012. Total employment is based on those 18–64 years old. Employment share by industry follow the Eurostat classification of industries group, see appendix A.1. Wages correspond to real log hourly wages in 2010 Swiss Francs and are taken from the SESS 1994–2010

Source: Swiss census 1970, 1990–2010, SESS 1994–2010, own calculations

in high-tech manufacturing and knowledge-intensive services. Paralleling the US experience (Autor and Dorn 2013), this highlights that regions with high-routine intensity are not only those with a high manufacturing share but also those with a larger skill-intensive service sector (see also the map in figure C1). We will explore differential impacts across sectors further in Section 4.4. Third, both the wage levels for all three education groups as well as wage differences between groups are higher in routine-intensive CZs. For instance, highly (middle) educated earn roughly

20 (8) Swiss Francs more per hour than the middle (low) educated whereas the same gap is 16 and 6 Swiss Francs in low routine regions in 1990. Fourth, consistent with higher earnings for more educated workers, high-routine regions had a slightly higher share of tertiary educated immigrants *already* in 1990 (18 versus 12%). This is consistent with the *positive sorting* documented in a cross-sectional analysis of cross-country migration (Grogger and Hanson 2011). Yet, the immigrants' overall skill mix is remarkably similar across the two regions, where the low-skilled share strongly dominates in the 1990s (56 and 61% of immigrants are low educated). The focus of this paper is on the *change* rather than the level, i.e., to which degree ICT *accentuated* the positive sorting of talent. Lastly, the time dimension in the table reveals that both regions' employment reduced during the 1990s, and strongly expanded between 2000 and 2010.

For ICT to have differential effects on workers with different education levels, they need to cluster in occupations with different task content. In table C10 we show — based on the task data from US DOT and Swiss census data from 1990 — that this is indeed the case. Each of the task measures is standardized to have a mean 0 and standard deviation 1. We observe that, in the general workforce, highly educated workers cluster in occupations with a high abstract and both a low routine and a low manual task content. The occupational specialization of workers with a middle education level has an above-average routine and below-average abstract and manual content. As expected, lower educated workers are most heavily employed in occupations with a high manual task content. In contrast to highly educated workers, they work in occupations that are also slightly below average in routine content.

Contrasting the specialization of highly educated immigrants to their group in the general workforce, we observe a similar abstract task content level and a slightly higher routine level, consistent with occupational downgrading at arrival (Dustmann et al. 2016). Among middle-educated immigrants, abstract task content is much lower, and both routine and manual task content considerably higher. Low-educated immigrants, in turn, show a low specialization in abstract, a high manual and also an above-average routine task specialization.

In sum, if ICT replaces employment in routine tasks and complements workers entrusted with abstract and cognitive tasks as Autor et al. (2003) argue, we would expect a positive effect on the demand for highly educated at the expense of middle-educated workers and an ambiguous effect on those with lower skills. Specifically, for immigrants, ICT substitution of routine tasks could affect both middle and low-educated immigrants due to the above-average specialization in these tasks in both groups.

4 Results

4.1 The skill-biased effect of technology on local labor market opportunities

Based on the conceptual framework in Section 2, we should observe that destination regions with higher skill-premia attract, ceteris paribus, more highly educated immigrants, if the latter sort themselves across destinations according to skill-related

Fig. 1 Smoothed changes in employment share 1990–2010 in percentiles of the 1990 wage distribution, for CZs above and below the median $\widetilde{RSH}_{r1970}$. *Note*: The figure plots the 20-year change in employment shares of occupations ranked by their skill percentile, separately for commuting zones above or below the median of the historical routine share $\widetilde{RSH}_{r1970}$. Following Autor and Dorn (2013), we construct skill percentile ranks of four-digit ISCO-2008 occupations computing their average real log hourly wages (in 2010 levels) based on the pooled SLFS years 1991–1993, using survey weights and hours worked. If an occupation contributes to more than one percentile rank, we allocate them based on their fraction of the occupation that maps into each percentile rank. We then simply calculate the difference between 2010 and 1990 employment shares within these percentile rank cells. *Source:* Swiss census 1970, SLFS 1991–1993 and 2009–2011, own calculations

economic opportunities. In this section, we present suggestive evidence that regions that were more exposed to ICT due to their historical industry specialization not only computerized more routine jobs and adopted more ICT (documented in Section 2.3) but also experience a differential change in economic opportunities (in both wages and employment) across the skill spectrum.

We start by analyzing how the relative employment opportunities changed with the regional routinization potential. Panel A of Fig. 1 depicts for each percentile of the skill distribution in 1990 the 20-year change in its employment share.[28]

Regions with an above-median routine employment share in 1970 (grey diamonds) are separately depicted from those below (black circles). These changes are remarkably similar in shape to those in the USA (cf. Autor and Dorn 2013; Autor 2015) at the top half of the skill distribution (as measured by the occupations' mean wages in 1990). In contrast to the US experience, however, the figure shows no strong employment growth at the bottom of the skill distribution. This highlights that the strong

[28]To allow comparison with a large literature, we followed the convention in the literature on labor market polarization and measured skill percentiles by the occupational mean log wages in 1990 (Acemoglu and Autor 2011).

growth in low-educated service jobs documented for the USA is possibly a specific feature in that context.

Panel B in Fig. 1 allows comparing the changes in employment observed among new immigrants to those for all workers (in panel A). We see that employment changes among new immigrants follow a similar pattern as the change in the overall employment distribution. In both panels, the reduction in the middle-paying occupations is more pronounced in high-routine areas. Yet, these changes are considerably more accentuated among new immigrants: the strong reduction in the middle, as well as the strongest increase at the top of the skill distribution, is 1.5 to 2 times as strong compared to the total workforce. The increase at the top of the wage distribution is more pronounced in high-routine areas both among natives and much more so for new immigrants. In contrast, high-routine areas also show a decrease in employment at the bottom of the wage distribution for immigrants, which is not present for the overall workforce. This might be explained by the fact that immigrants in the lowest skill groups were also employed in occupations with a high-routine task content, as documented in Section 3.3. More concretely, table C9 shows the change in the occupational structure among immigrants. The typical new immigrant in 1990 worked in low-paid occupations such as crafts and related trades, service, and elementary occupations. By 2010, regions with higher ICT exposure experienced stronger growth particularly among highly paid professionals, which became the largest occupation group, and to a lesser degree among managers and technicians. These regions also saw a stronger reduction in middle-paying occupations such as craft workers.

In sum, we observe polarization in the upper half of the skill spectrum but much less so at the bottom. These employment changes are generally more pronounced for new immigrants compared to the overall workforce (implicitly more than those of natives). We interpret this as the first evidence that the entry of skilled immigrants is an important adjustment channel to these long-run technological changes. This adds an interesting new perspective on Borjas's 2001 hypothesis that immigrants act as arbitrageurs of economic opportunities and thus grease the wheel of the labor market. Recent evidence for this hypothesis has been presented by Cadena and Kovak (2016) for the case of low-skilled immigrants in the USA. In contrast to the experience from the US context (Autor and Dorn 2013; Basso et al. 2020), we observe no strong growth at the bottom of the skill distribution neither overall nor by new immigrants, but strong differential employment growth in the upper half.

Next, we evaluate whether changes in employment opportunities are paralleled by changes in the relative wages across skill groups. To this end, we investigate how workers' wages evolved across local labor markets and education groups. Given the clustering of workers with heterogeneous skills in occupations with different task content (cf. table C10), we expect the high-to-middle wage premium to increase. Table 2 presents the results of a reduced form regression testing this hypothesis, analogous to the (first stage) estimation of our main specification (4). The dependent variable is the change in the wage difference between highly educated and middle-educated workers (panel A) or middle- and low-educated workers

Table 2 Effect of ICT exposure on relative wages: 2SLS

Dependent variable: Differences in residual wages estimated in stacked decadal differences	Wages		Log wages	
	(1)	(2)	(3)	(4)
Panel A: High/Middle educated				
$\widetilde{RSH}_{r1970}$	10.112	10.996	0.187	0.254
	(4.919)	(5.042)	(0.078)	(0.085)
Panel B: Middle/Low educated				
$\widetilde{RSH}_{r1970}$	2.232	− 4.362	0.063	− 0.128
	(1.958)	(2.126)	(0.064)	(0.073)
N	210	210	210	210
Covariates		✓		✓

Notes: This table shows the effect of the historical routine specialization in 1970, $\widetilde{RSH}_{r1970}$, on the stacked changes (1994–2000, 2000–2010) in the difference of the average wage (in absolute levels or logs), $\Delta(w^{j}_{rt} - w^{j-1}_{rt})$, of highly educated and middle-educated individuals (panel A) and middle- and low-educated individuals (panel B). Regressions include fixed effects for Cantons, decades, and Nuts II regions and covariates as specified in Table 4 (column 6). Standard errors in parentheses are clustered by CZ. Wage measures are based on SESS data as described in Appendix A.1

Source: Swiss census 1970, 1990–2010, SESS 1994, 2000, and 2010, own calculations

(panel B).[29] The table presents the coefficient estimates for our instrument, the routine share measure in 1970. The wage difference is calculated by each education group's average wage in levels and logs, pooling native and immigrant workers. Columns 1 and 3 report estimates with specifications including fixed effects only, whereas columns 2 and 4 also include commuting zone characteristics (which we discuss in detail below). Note that our wage data is based on a relatively small self-reported survey; therefore, we interpret these results, although strongly consistent, cautiously as suggestive evidence.

Keeping this limitation in mind, the estimates in panel A indicate that ICT exposure indeed had a strong positive effect on returns to education. The estimate in column 2 (and 4), for instance, indicates that a one percentage point higher routine share in 1970 is significantly associated with the average hourly wage difference between those groups by roughly 10 Swiss Francs (0.18%) in one decade. Economically, this is a meaningful effect: the corresponding hourly wage difference grew by 2.5% more ($0.25 \times 5(IQR) \times 2$ decades) on average in CZs at the 75th percentile compared to a CZ at the 25th percentile of the initial routine share distribution between

[29] To avoid spurious effects from demographic trends, we purge wages from individual-level demographic characteristics. We do this by obtaining the residuals from a regression of individual-level wages (in absolute levels or logs) on a rich set of demographic variables (dummies for gender, marital status, immigrant status, and cubics in potential labor market experience) each year. These residuals are averaged by education level, CZ, and year, analogous to our main specification.

1990 and 2010. In contrast to the effect on the top end of the wage distribution, we do not find a significant or even a negative association of the historical routinization on the wage difference at the lower end of the wage distribution, i.e., between middle- and low-educated workers.

Taken together, the evidence presented in Fig. 1 and Table 2 suggests that in areas with higher ICT exposure both earnings and employment opportunities for workers at the top of the skill distribution increased relative to the middle. Consequently, we expect highly educated immigrants to sort themselves into those regions while observing a relative reduction in the inflow of middle-educated. The lack of differential changes in the lower parts of the skill distribution suggests small or no relative effects between these groups.

4.2 Skill-biased technical change and high-skilled migration

Turning to our main analysis of the endogenous response in the skill mix of recent immigrants. Figure 2 shows the descriptive total number of new immigrants by education group in each decade from 1990 to 2010. CZs are grouped into quartiles (Panel A to D) of the pre-ICT specialization in routine occupations in 1970.

This figure visualizes our main story remarkably. First, total immigration to Switzerland increased considerably from 1990 to 2010, and more than doubled over the two decades, from roughly 230 to 500 thousand (cf. also Table 1). Second, the evolution was very heterogeneous across skill groups. In all regions, the number of highly educated migrants was smaller than those of middle or low educated in 1990. In later years, they grew substantially, overtaking the other skill groups by 2010 in all but the lowest quartile. In contrast, both the inflow of middle- and low-educated migrants contracted between 1990 and 2000 and grew much slower thereafter (compared to highly educated). Third, these trends are much more pronounced in CZs

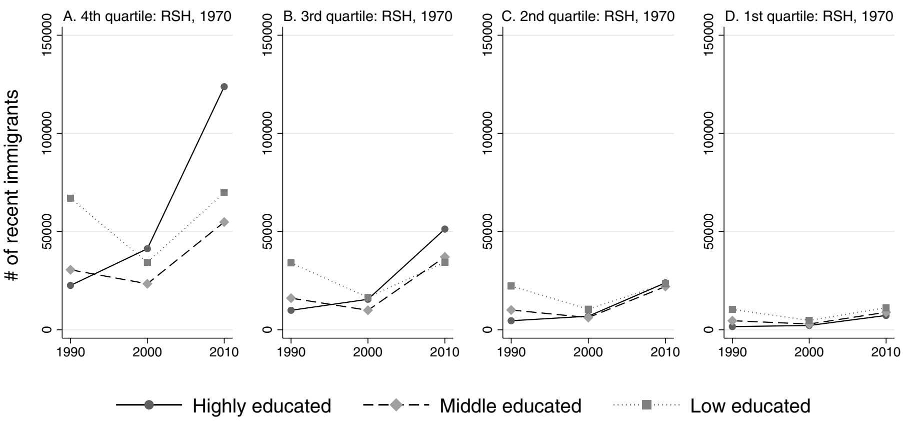

Fig. 2 Total number of recent migrants by education and $\widetilde{RSH}_{r1970}$ quartiles. *Note:* This figure plots the total number of recent immigrants by education group (high, middle, low), separately for commuting zones in each quartile of the historical routine share $\widetilde{RSH}_{r1970}$ (Panel A to D). *Source:* Swiss census 1970, 1990–2010, own calculations

with a higher routine share in 1970 and fall throughout all panels, which is a remarkable result pointing to the consistency of our proposed channels. Even more so, the inflow of highly educated migrants grew progressively more between 1990 and 2000 in high-RSH regions, while the inflow of less-educated contracted strongly. Between 2000 and 2010, high-routine CZs experienced a substantial acceleration in the inflow of highly educated while the inflow of lower educated groups grew, but to a much smaller extent. In CZs with the lowest routine-content, however, all education groups grew slightly more strongly but more similar in the last decade. It is striking that our hypothesis is evident already in these descriptive plots where along the quartiles, there is an obvious increase in the growth of high relative to middle-educated. Worth noting, the strong growth in the (overall) number of immigrants in the 2000s might reflect the implementation of the FMP policy, a point to which we return below. Lastly, we can observe that the share and number of low-educated immigrants settling in high-routine share areas was very high in 1990.

Table 3 presents our main results, i.e., the estimated effect, τ, of routine specialization from regression specification (4). In each regression (columns 1–3 and 5), we instrument RSH_{rt} with its historical share $\widetilde{RSH}_{r1970}$ and include fixed effects at the level of Cantons and origin-country-by-decade. We use two-way clustered standard errors at the CZ and source country level as these might be correlated and are not nested (Cameron et al. 2011).[30] The regressions include 33 source countries in 106 CZs, 2 decadal differences (stacked), and are estimated separately for high-vs-middle (panel A) and middle-vs-low educated (panel B). Panel C, D, and E show the decomposition into separate estimates for the change in the number of highly educated, middle-educated, and low-educated immigrants as dependent variables, respectively.

The results again confirm our previous conjectures. Column 1 in panel A shows that a one percentage point higher routine share implies a 1.4% increase of highly educated relative to middle-educated immigrants between 1990 and 2000. This effect is statistically significant and even increases in the following decade to 3.2% (column 2).[31]

Column 3 stacks the decadal changes in the education ratios which produces a statistically significant average effect of 2.2%. The impact on the skill mix of immigrants is also economically meaningful: CZs with a 5 percentage points (roughly the interquartile range in the 1990s, cf. table C1) higher initial routine specialization experienced an approximately 11% larger inflow of immigrants with high relative to middle education per decade. The estimates in panel B, in contrast, show that ICT did not have a significant effect on the relative inflow of middle-to-low-educated

[30] Note that using origin-decade fixed effects and clustering standard errors is analogous to using regressions based on data aggregating all immigrants at the level of CZs. Hence, these recessions essentially use variation across 106 CZs and 2 decades. Since we will augment these regressions below with origin country-specific variables, we use disaggregated data for consistency throughout (for a detailed discussion on using aggregate variables in non-aggregate models, see Lang and Gottschalk 1996). All regressions are unweighted following Solon et al. (2015). Table C8 shows results are qualitatively similar if we use (beginning of period) destination region population weights.

[31] Note that the effects in the second decade (2000–2010) is not statistically different from the effect in the first decade (1990–2000) when we test this in a regression including the RSH variable interacted with a dummy for the second decade.

Table 3 Effect of ICT exposure on skill composition of new immigrants: 2SLS and OLS

Dependent variable: Differences in log numbers and ratios of recent immigrants by education group	2SLS			OLS	2SLS
	1990–2000	2000–2010	Stacked		1970–1980
	(1)	(2)	(3)	(4)	(5)
Difference in log ratios					
Panel A: High/Middle educated					
RSH_{rt}	1.397	3.195	2.232	2.665	0.125
	(0.568)	(1.847)	(0.975)	(0.768)	(0.305)
Panel B: Middle/Low educated					
RSH_{rt}	0.417	− 1.397	− 0.425	− 0.485	− 0.096
	(0.503)	(1.060)	(0.520)	(0.435)	(0.219)
Difference in log numbers					
Panel C: High educated					
RSH_{rt}	0.423	3.122	1.677	1.860	− 0.506
	(0.723)	(1.814)	(1.043)	(0.791)	(0.296)
Panel D: Middle educated					
RSH_{rt}	− 0.974	− 0.073	− 0.556	− 0.805	− 0.631
	(0.655)	(0.915)	(0.397)	(0.396)	(0.428)
Panel E: Low educated					
RSH_{rt}	− 1.391	1.324	− 0.131	− 0.321	− 0.535
	(0.575)	(0.966)	(0.564)	(0.510)	(0.408)
N	3,498	3,498	6,996	6,996	3,498
First stage: F-statistic (p-value)	65.2(0.00)	67.0(0.00)	71.4(0.00)		216.6(0.00)

Notes: This table shows the effect of higher routine share on the change in the log ratio of new immigrants with high and middle education level (panel A), middle and low education (panel B), and separately for the change in the log number of immigrants by education level (panels C–E), based on Eq. (4). Columns 1 and 2 show the effect on the change in the number of immigrants from 1990 to 2000 and 2000 to 2010, respectively. Columns 3 and 4 stack the changes of both decades in one regression. In columns 1–3 and column 5, the beginning of period routine share, RSH_{rt}, is instrumented with its historical routine specialization in 1970, $\widetilde{RSH}_{r1970}$. Column 4 shows the OLS effect. Column 5 shows the effect on the change in the number of immigrants by education level from 1970 to 1980. Regressions include fixed effects for Cantons, origin countries, decades, and origin-decades-interactions and standard errors are clustered by CZ and origin country

Source: Swiss census 1970, 1990–2010, own calculations immigrants. Column 4 provides OLS estimates, which are slightly larger than the 2SLS estimates. This suggests that IV leads to a more conservative estimates of the impact of ICT exposure on the inflow of highly educated immigrants. The small difference between IV and OLS (akin findings in Autor and Dorn 2013) suggests that there is little endogeneity remaining after conditioning on our very large set of fixed effects.

Column 5 performs an important placebo test: the local routine share is *not* correlated with changes in the skill mix of new immigrants in the 1970s, the last decade *before* the acceleration in the fall of computing prices and widespread ICT adoption. This highlights that the regions with higher routine specialization essentially attracted *similar* amounts of highly educated immigrants (relative to middle educated) in the 1970s when ICT adoption was relatively low. This lends further credibility that our identification strategy indeed picks up an effect of exposure to computerization.

Decomposing these relative effects in panels C–E reveals first that a higher initial routine share is associated with a larger inflow of highly educated immigrants throughout both periods, particularly between 2000 and 2010.[32] Second, ICT exposure is associated with weaker inflows of middle-educated immigrants in both periods. Thus, the strong positive effect we find in panel A is, in fact, a combination of a positive effect on high and a negative one on middle-educated immigrants. Third, the disaggregation by decade shows that the positive effect in panel A results from a greater negative effect on middle educated between 1990 and 2000. Between 2000 and 2010, the strong positive effect on the highly educated dominates. Fourth, ICT exposure led to a significant reduction in the number of low-educated immigrants between 1990 and 2000 and had a positive but insignificant effect on their number between 2000 and 2010. The negative effect on the low-educated in the first decade can be rationalized, as mentioned above, by the fact that a substantial part of this group was employed in routine-intensive occupations in 1990 which were subsequently automated. Automation might have been facilitated by the generally low economic performance in this decade. Evidence from the USA suggests that routine-biased technical change accelerates during economic downturns (Hershbein and Kahn 2018). In sum, the combined effects in panels A and B are a result of mostly negative effects on the middle and low end of the skill spectrum between 1990 and 2000. After 2000, ICT induced stronger growth at the poles of the skill distribution, particularly at the top end.

4.3 Robustness

Next to historical routine task specialization, several other factors might explain why some regions experience stronger inflows of highly educated immigrants. We assess these factors in Table 4 by augmenting specification (4) with covariates at the level of CZs considered important in the literature on bilateral migration and job polarization which have not already been differenced out or absorbed in the Canton fixed effects.[33]

[32] The estimates in panel A (and B) can be expressed as a linear combination of the estimated effects in panels C and D (D and E, respectively).

[33] By including dyadic covariates such as migrant networks the source dimension becomes important, consequently, an aggregate regression would not yield identical results, cf. Footnote 30.

Table 4 Robustness of effect of ICT exposure on skill composition of new immigrants: 2SLS

Dependent variable: Stacked decadal differences in log numbers and ratios by education group									
							Workers		
	Population						All	Manu.	Service
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Difference in log ratios									
Panel A: High/Middle educated									
RSH_{rt}	1.612	2.275	1.840	2.103	3.953	2.824	3.077	1.032	2.781
	(0.880)	(0.982)	(0.895)	(0.995)	(0.692)	(0.752)	(0.598)	(0.596)	(0.743)
University City$_r$	0.329					0.174	0.138	0.117	0.171
	(0.063)					(0.054)	(0.073)	(0.071)	(0.078)
Share N_{rs1970}		− 2.023				− 2.216	− 0.758	1.645	0.287
		(0.917)				(1.004)	(1.609)	(2.245)	(1.460)
Share E^3_{rs1970}			0.200			0.140	0.091	− 0.012	0.087
			(0.062)			(0.057)	(0.039)	(0.041)	(0.034)
Share E^2_{rs1970}			0.161			0.112	0.074	0.035	0.068
			(0.071)			(0.066)	(0.046)	(0.045)	(0.037)
Offshoring potential$_{rt}$				0.038		0.019	0.003	0.044	− 0.017
				(0.034)		(0.032)	(0.035)	(0.024)	(0.033)
Share manufacturing$_{rt}$					− 1.531	− 1.076	− 0.924	− 0.049	− 1.114
					(0.422)	(0.395)	(0.384)	(0.240)	(0.380)

Table 4 (continued)

Dependent variable: Stacked decadal differences in log numbers and ratios by education group

	Population						Workers		
							All	Manu.	Service
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Panel B: Middle/Low educated									
RSH_{rt}	− 0.497	− 0.458	− 0.417	− 0.268	0.421	0.932	0.552	0.392	0.379
	(0.513)	(0.530)	(0.552)	(0.523)	(0.543)	(0.685)	(0.646)	(0.408)	(0.566)
University City$_r$	0.038					− 0.053	0.046	− 0.018	0.087
	(0.075)					(0.088)	(0.085)	(0.043)	(0.077)
Share N_{rs1970}		1.542				1.211	1.393	2.256	2.640
		(0.872)				(0.771)	(0.956)	(0.726)	(0.779)
Share E^3_{rs1970}			− 0.040			− 0.067	− 0.037	− 0.015	− 0.027
			(0.063)			(0.064)	(0.040)	(0.020)	(0.042)
Share E^2_{rs1970}			0.033			0.010	− 0.013	− 0.052	0.004
			(0.060)			(0.058)	(0.049)	(0.030)	(0.049)
Offshoring potential$_{rt}$				− 0.046		− 0.053	− 0.010	− 0.008	− 0.013
				(0.035)		(0.035)	(0.023)	(0.013)	(0.023)
Share manufacturing$_{rt}$					− 0.753	− 0.926	− 0.459	− 0.188	− 0.364
					(0.271)	(0.338)	(0.310)	(0.205)	(0.274)
Difference in log numbers									
Panel C: High educated									
RSH_{rt}	1.082	1.571	1.385	1.574	3.683	2.799	1.983	0.270	1.666
	(0.962)	(1.041)	(0.995)	(1.057)	(0.667)	(0.754)	(0.614)	(0.589)	(0.676)

Table 4 (continued)

Dependent variable: Stacked decadal differences in log numbers and ratios by education group

	Population						Workers		
							All	Manu.	Service
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Panel D: Middle educated									
RSH_{rt}	− 0.530	− 0.704	− 0.456	− 0.529	− 0.270	− 0.026	− 1.094	− 0.762	− 1.115
	(0.396)	(0.402)	(0.405)	(0.402)	(0.445)	(0.508)	(0.461)	(0.394)	(0.481)
Panel E: Low educated									
RSH_{rt}	− 0.033	− 0.246	− 0.039	− 0.261	− 0.691	− 0.957	− 1.645	− 1.154	− 1.494
	(0.530)	(0.564)	(0.561)	(0.569)	(0.646)	(0.672)	(0.766)	(0.637)	(0.634)
N	6,996	6,996	6,996	6,996	6,996	6,996	6,784	6,784	6,784

Notes: This table shows the effect of higher routine share on the change in the log ratio of the number of new immigrants with high and middle education level (panel A), middle and low education (panel B), and separately for the change in the log number by education level (panel C–E), based on Eq. (4). Changes in the number of immigrants by education by decade (1990–2000, 2000–2010) are stacked in one regression with the beginning of period routine share, RSH_{rt}, instrumented with its historical routine specialization in 1970, $\widetilde{RSH}_{r1970}$. Column 1 to 6 shows the effect on the full population of new immigrants and column 7 to 9 on new immigrant workers by sector of employment. Columns 1 and 2 include an indicator for a University city and the share of an origin country on the total number of immigrants, respectively. Column 3 includes each origin countries share of highly educated and middle-educated immigrants in 1970. Columns 4 and 5, respectively, include Blinder and Krueger's (2013) measure for potential offshoring (as described in Appendix A.1) and the local employment share of manufacturing. Column 6 uses all variables jointly. Covariates correspond to the beginning of period values. Regressions include fixed effects for Cantons, origin countries, decades, and origin-decades-interactions and standard errors are clustered by CZ and origin country

Source: Swiss census 1970, 1990–2010, own calculations

In column 1, we include an indicator for CZs in which a university was established prior to 1990.[34] The literature suggested that opportunities for university education might provide an entry to a local labor market for highly educated immigrant workers (Grogger and Hanson 2013; Kato and Sparber 2013). Indeed, the estimated coefficient suggests that CZs with a university attract more highly relative to middle educated. Since most universities in Switzerland are located in larger cities, this effect could also be consistent with an agglomeration effect, i.e., individual workers enhancing each other's productivity (and wages) by working close to other skilled individuals as suggested by Kerr et al. (2016) and Moretti (2004).[35]

In column 2, we test the importance of ethnic networks in explaining differential skill-inflow. While gains in educational attainment in origin countries are absorbed in the fixed effects, local changes in immigrants' skill mix might still be affected by pre-existing networks that facilitate their economic integration or provide some sort of amenity or information about the destination environment (Card 2001; Patel and Vella 2013). In line with this hypothesis, our measure of networks, the share of immigrants from the respective source countries in 1970, raises the share of middle-educated immigrants relative to both highly educated and low-educated immigrants. As an additional hypothesis, we test whether destinations with initially very low levels of highly educated immigrants subsequently experience larger inflows from them, simply due to mean reversion as pointed out by Michaels et al. (2014). Column 3 shows that the previous results are unaffected when we control for the initial share of both highly educated and middle-educated by origin country in 1970 which also accounts for the low-educated share.

The impact of offshoring and trade with low-wage countries has been discussed in the literature as an important alternative factor affecting the local relative demand for skills (Goos et al. 2014; Dauth et al. 2014; Autor et al. 2013; 2015). Specifically, firms might move offshorable tasks abroad to lower wage countries while focusing more on higher skilled tasks at home. Jobs that are more easily offshorable might also also be more intensive in routine tasks.[36] In column 4, we include a proxy from Blinder and Krueger (2013) on how susceptible local employment is to offshoring.[37] The

[34]Prior to 1990, the following CZs contained a university: Basel, Bern, Fribourg, Geneva, Neuchâtel, Lausanne, St.Gallen, Zurich.

[35]Note that the presence of universities could also raise the skill supply of natives which could mediate the response of immigrants depending on the degree of imperfect substitutability between natives and immigrants and the size of human capital externalities.

[36]In our data, the correlation between task offshorability and routine intensity is relatively low ($\rho = -0.096$) at the local level.

[37]We follow the convention in the literature on controlling for the *potential to offshore* a specific task and not for *actual offshoring* as the latter could be itself an outcome from the technical displacement of routine occupations. We use Blinder and Krueger's (2013) measure for offshoring potential based on worker characteristics such as occupations and education levels (see details of construction in Appendix A.1. To complement this analysis, table C8 (columns 6 and 7) shows that our main estimate is qualitatively similar if we include a measure of Chinese import penetration inspired by Autor et al. (2013). This is interesting, as the importance of trade with China grew after China's WTO accession in 2001 and had differential effects on workers by skill in other countries, e.g., in Germany (Dauth et al. 2014) or Norway (Balsvik et al. 2015).

estimates are very small and statistically insignificant and leave our main estimate unaffected.

Relatedly, we test in column 5 for an effect of a CZ's initial share of employment in manufacturing (Gould 2019). The estimated coefficient shows that a higher manufacturing share increases the inflow from lower education groups, i.e., lowering both the high-to-middle and middle-to-low educated ratio. Interestingly, however, including this control increases the effect of ICT exposure on both high-to-middle-educated and middle-to-low-educated immigrants. In other words, when we compare regions with a similar manufacturing share, those with a higher routine specialization experience even faster growth of highly educated relative to middle-educated immigrants. We will discuss the manufacturing sector's role in more detail in the next section.

Column 6 presents a robust effect of initial routine specialization when we include the full set of explanatory variables in the model. The estimated impact on the high-to-middle educated ratio increases considerably, which translates into an economically large effect. At the interquartile range of the 1990 routine specialization, more routine-intensive regions experienced roughly a 14 (5×2.824) % larger inflow in the number of highly educated immigrants relative to those with middle education per decade. In contrast, the effect on the middle-to-low educated ratio is small and not statistically significant.

We performed several additional robustness checks to test the sensitivity of our results with respect to changes in specification and samples. First, table C5 shows qualitatively similar results if we run our main specification with data collapsed at the municipality instead of the CZ level which allows including CZ fixed effects. Second, based on our baseline CZ-level sample, table C8 explores robustness when using the number of immigrants at the beginning of the period to weight cells, using the inverse hyperbolic sine instead of the log transformation for the dependent variable, dropping immigrants in the missing origin country category, keeping only immigrants in prime-age (below 50), and using only natives to construct the contemporaneous routine share variable in 1990 and 2000 or its instrument based on the 1970 industry specialization, or using both. All of these tests yield qualitatively similar results. A third concern is that strong inflows of mostly highly educated cross-border workers in regions close to the Swiss border, as shown in Beerli et al. (2021), might crowd out some of the responses of new immigrants. Table C6 shows that both the border and the non-border region experienced similar inflows as we observe in the whole sample of regions. While the point estimate of the effect on middle-to-low-educated immigrants differs across regions, neither this effect nor the effect on high-to-middle educated immigrants is significantly different across regions.

In sum, these results highlight that changing labor market opportunities strongly affect which types of immigrants choose to settle in destination regions. Local ICT exposure induced a much stronger inflow of highly relative to middle-educated immigrants. Echoing existing evidence that the ICT-induced growth in high-paying abstract occupations is mainly driven by the labor market entry of young workers (as opposed to old workers) in the USA (Autor and Dorn 2009). Our findings point to the recruitment of international migrants as another, most likely, faster adjustment channel. In addition, our results imply a strong technology-skill complementarity where highly educated immigrants follow technology. Highlighting a different perspective of this complementarity, Lewis (2011) presented evidence that inflows of low-skilled immigrants delayed the adoption of automation technology in the USA. Our results imply that also the supply of skills may follow technology. Of course, it is warranted to ask, which comes first. We believe that our results are unlikely to be driven by reverse causality as we exploit only the pre-determined variation in ICT exposure and control for existing immigrant networks. Also, the fact that the share of low-skilled was very high in highly exposed regions in 1990 (cf. Table 1) runs counter this argument.

4.4 Heterogeneity in sorting across sectors

Next, we examine whether the exposure to technology affects the skill mix of immigrants differently in the manufacturing and the service sector. The structural changes in the sectoral level brought about by ICT have been assessed for non-immigrant populations in the USA (Autor et al. 2015), for instance, find that ICT, in the form of automation capital, reduced routine employment among production workers in the manufacturing sector in the 1980s. In subsequent decades, the effect of ICT, in the form of computers, was increasingly concentrated in the service sector reducing routine (cognitive) employment, e.g., in clerical occupations. Complementary evidence by Gould (2019) underscores that the decline of manufacturing is an important labor market disruption affecting relatively low-skilled workers in relatively well-paying jobs.

To investigate heterogeneous effects across sectors, columns 7 to 9 in Table 4 present estimates from regressions for the subsample of workers by industry of employment analogous to specifications to the full immigrant population. Compared to the effect on the full population in column 6, the estimates in column 7 show a somewhat stronger effect of ICT exposure on the inflow of highly relative to middle immigrants in the total workforce. This confirms that economic opportunities affect workers and not necessarily people outside of the workforce, which reinforces our confidence in our proposed causal mechanism of labor market incentives. The effect is composed of a slightly weaker effect on the inflow of highly educated workers and a much stronger and significant negative effect on middle and low-educated workers.[38] When we split immigrant workers into those employed in manufacturing (column 8) and services (column 9), it is evident that the effect of ICT exposure is most prominent in the latter. In the manufacturing sector, we only find a strong negative effect on middle-educated immigrants while the positive effect on highly educated is more muted (panels C and D in column 8). Together, this produces a much weaker and insignificant effect on the relative inflow of high-to-middle-educated immigrants in the manufacturing sector (panel A in column 8). The effect of ICT on the inflow of middle-educated relative to low-educated immigrants is never significant. In the previous section, we found that the regional manufacturing share is negatively associated with the change in the high-to-middle educated ratio. The result

[38] In addition, we show in table C12 that this negative effect is most pronounced in the first decade (1990–2000) when Switzerland experienced only modest overall economic growth.

in column 8 suggests that routinization changed the skill mix of immigrants more in the service than in the manufacturing sector.

In sum, these results suggest that although present in both sectors and regions, the ability to attract foreign-born talent due to computerization is most pronounced in the service sector and in regions specialized in services.

4.5 Source country heterogeneity and the role of the Free Movement of Persons policy

An important motivation of immigration policies is facilitating the entry of workers whose skills are scarce in the national labor market. Given the evidence presented above, a relevant question from a policy perspective is *whether* and *how* the response of immigrants to economic incentives changes when immigration restrictions are altered decisively. The Swiss experience between 1990 and 2010 is interesting in this regard as it allows evaluating the effects of the introduction of a free movement policy. As explained above, immigration restrictions for EU residents were progressively abolished after 2002, allowing them to adopt work unrestrictedly in Switzerland after 2007. In contrast, immigration from non-EU countries remained subject to quotas and further administrative hurdles. In this section, we answer two questions: (i) to which degree, if at all, did the lower cost of immigration for EU residents affect the skill mix of immigrants? and, (ii) did the openness allow immigrants to respond more strongly to local demand for skills?

Figure 3 presents the effects of the policy by plotting the number of new immigrants from each education group in each decade, separately for CZs above and below the median routine share in 1970, and separately for immigrants from EU countries (panels A and B) and non-EU countries (panels C and D). Roughly the same trends are evident as in Fig. 2: i.e., CZs with a routine share above the median experience a stronger inflow of highly relative to middle-educated immigrants. Yet, the number of immigrants from EU countries increased much stronger between 2000 and 2010 compared to those from non-EU countries, as one would expect given lower immigration restrictions. Moreover, the larger inflow among EU immigrants is particularly pronounced in CZs with above-median routine share. Hence, this descriptive evidence suggests that the policy increased the inflow of immigrants from EU countries and likely induced stronger inflows to regions with higher skill demand.

Empirically, we evaluate the effects of this policy by including an indicator for the FMP in Eq. (4), where FMP_{st} is an interaction of a dummy for immigrants from European origin countries and a dummy for the decade between 2000 and 2010, i.e., $1(s = EU) \times 1(t = 2000)$. In this regression, we measure whether the skill mix changes differently with the FMP policy for immigrants from the EU compared to immigrants from non-EU countries, irrespective of their destination within Switzerland. Since origin and time fixed effects absorb differential effects by decade and origin country trends, this effect is identified as the difference-in-difference effect where non-EU immigrants serve as a control group. Importantly, the identification of this effect hinges on the assumption of a parallel trend, i.e., that there are no changes affecting EU and non-EU immigration other than the policy. To support the validity of this assumption, we include a rich set of source-by-decade control variables, as it is a

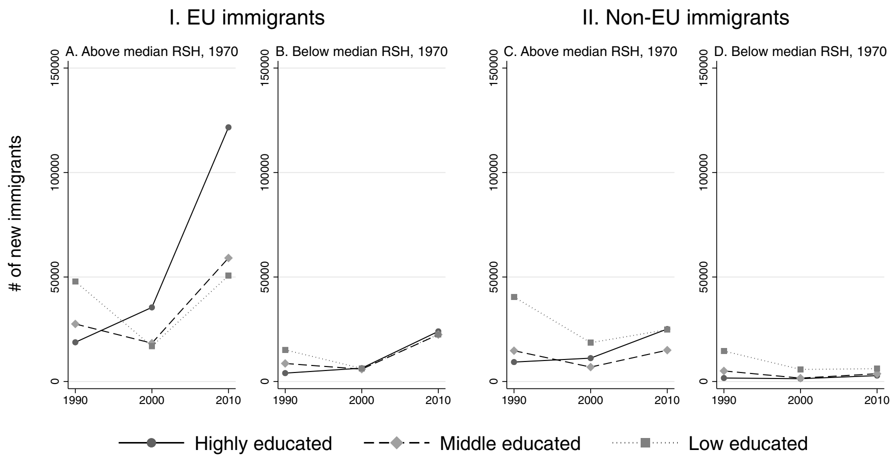

Fig. 3 Total number of recent immigrants by skill by $\widetilde{RSH}_{r1970}$ areas and source country. *Note:* This figure plots the total number of recent immigrants by education group (high, middle, low) from European and Non-European countries, separately for commuting zones above and below the median of the historical routine share $\widetilde{RSH}_{r1970}$. We drop immigrants with missing source country information, from Poland, Romania, Hungary, and (former) Czechoslovakia which became EU member states within the time of analysis (results are not driven by this exclusion). *Source:* Swiss census 1970, 1990–2010, own calculations

standard in the international migration literature (see, inter alia, Mayda 2010; Ortega and Peri 2013).[39] We are, however, hesitant to interpret this effect as causal, since the stable unit treatment value assumption (SUTVA) may be violated, e.g., if larger inflows of EU citizens crowd out (or crowd in) non-EU immigrants. Even without a fully causal interpretation, this is a policy-relevant comparison providing suggestive evidence on how an immigration policy can moderate the response of immigrants to long-run labor demand shifts.

Table 5 presents the results of the augmented regressions. In columns 1 and 2, the dependent variable is the change in the log ratio of highly educated relative to middle-educated immigrants and middle-educated relative to low-educated immigrants as before, respectively. Columns 3–5 show results when the outcome is the log difference in the number of new immigrants with a high, middle, and low education level, respectively. In panel A, we allow the policy to have only a direct effect on immigration. Focusing first on the coefficient of RSH_{rt} in panel A, we observe that the

[39] In particular, we include the following variables with origin-country decade variation: the decadal changes in an origin country's Gini coefficient to measure inequality, in its PolityIV score to measure political for civil rights protection, in its GDP per capita, and an indicator for whether there was a conflict in the source country that could increase the number of asylum seekers. To control for changes in the skill supply by source country, we include the decadal changes in the log ratio of the high-to-middle-educated (column 1) and the middle-to-low-educated (column 2) origin country population, and the change in the population log number by education (columns 3–5). Note that due to the inclusion of skill-specific source country controls, the coefficient estimate in column 1 (column 2) can only be decomposed approximatively (but not precisely) be into the estimates in columns 3 and 4 (columns 4 and 5), respectively. See Appendix A.1 for the construction of these variables and table C13 for their coefficient estimates.

Table 5 Effect of ICT exposure and Free Movement Policy on skill composition of new immigrants: 2SLS

Dependent variable: Stacked decadal differences in log numbers and ratios by educated group	Difference in log ratios		Differences in log numbers		
	High/Mid	Mid/Low	High	Middle	Low
	(1)	(2)	(3)	(4)	(5)
Panel a: direct effect of migration policy					
RSH_{rt}	3.318	0.720	3.309	− 0.009	− 0.729
	(0.768)	(0.761)	(0.807)	(0.579)	(0.748)
FMP_{st}	− 0.065	0.016	0.392	0.499	0.309
	(0.187)	(0.105)	(0.148)	(0.216)	(0.222)
Panel b: interaction effect of migration policy with skill demand					
RSH_{rt}	2.974	0.776	2.365	− 0.609	− 1.385
	(0.613)	(0.787)	(0.728)	(0.784)	(0.834)
$RSH_{rt} \cdot FMP_{st}$	1.372	− 0.227	3.762	2.390	2.617
	(1.605)	(1.285)	(2.004)	(1.564)	(1.851)
N	5,936	5,936	5,936	5,936	5,936
Covariates$_{rst}$	✓	✓	✓	✓	✓

Notes: This table shows the effect of higher routine share on the change in the log ratio of the number of new immigrants with high and middle education level (column 1), middle and low education (column 2), and separately for the change in the log number of new immigrants by education level (columns 3–5), based on Eq. (4). Changes in the number of immigrants by education by decade (1990–2000, 2000–2010) are stacked in one regression with the beginning of period routine share, RSH_{rt}, instrumented with its historical routine specialization in 1970, $\widetilde{RSH}_{r1970}$. Regressions in panel A include a dummy for European origin countries interacted with a dummy for the decade 2000–2010, i.e., $FMP_{st} = 1(s = EU) \times 1(t = 2000)$. These regressions omit origin-by-decade fixed effects and include instead origin-by-decade controls for push factors, i.e., decadal changes in the GINI coefficient, real GDP per capita, the Polity4 score, a conflict dummy, and decadal changes in the log ratio of the high-to-middle-educated (column 1) and the middle-to-low-educated (column 2) origin country population, and the change the population log number by education (columns 3–5), see details in appendix A.1. In regressions in panel B, FMP_{st} is interacted with the routine share variable and instrumented with $\widetilde{RSH}_{r1970} \cdot FMP_{st}$. The main effect of the FMP variable is absorbed by source-by-decade fixed effects. All regressions include the covariates from Table 4 column 6. We dropped the EU10 members which changed their EU status between 2000 and 2010; the results are robust so they are included in the policy group

Source: Swiss census 1970, 1990–2010, own calculations

estimates presented here are of roughly the same magnitude as our baseline estimate (in Table 4). This assures that the included origin country covariates capture most of the source-by-decade effects. The estimated coefficient of FMP_{st} is positive and large when each education group is considered separately. This suggests that policy increased the inflow of immigrants from EU countries in all three education groups by roughly 35 to 49% relative to those from non-EU countries. For the group of highly educated immigrants, the policy effect has a similar magnitude as a 10-percentage point higher routine share would produce (roughly 2 times the interquartile range).

These effects are economically large for all education groups. Their similar size, however, explains why the effect of the policy on the *relative* inflow by education groups is not statistically significant (shown in columns 1 and 2).

Panel B allows for an interaction effect with the local routine specialization, as Fig. 3 suggests.[40] This interaction term allows evaluating whether the inflow of immigrants by education group from the EU to regions with large skill demands was different after the policy was implemented. We find that CZs with higher ICT exposure experienced larger inflows of immigrants from all education groups as represented by the generally positive effects of the interaction term $RSH_{rt} \cdot FMP_{st}$ in columns 3–5. However, this interaction effect is only significant for the highly educated group. This indicates that regions with a higher ICT exposure were able to attract even more highly educated immigrants from EU countries after the free movement policy was implemented. Although this effect is also positive for two other education groups, it is roughly one percentage point smaller and neither statistically significant nor different from the effect on highly educated. This is why we cannot rule out that the policy did not affect the *relative* inflow of immigrants from different education groups as indicated by the insignificant coefficient of the interaction term (in columns 1 and 2).

Taken together, these results suggest that, at the national level, the policy led to a significantly larger inflow of immigrants from all education groups. Inspecting heterogeneous effects by region, we observe that the policy has not altered the relative flow of highly educated immigrants to regions with strong ICT-induced skill-demand. If anything, the policy allowed regions with stronger demand to attract even more highly educated immigrants after immigration restrictions were abolished. Our findings complement the evidence presented in Beerli et al. (2021), who find that the FMP policy led to a strong inflow of mostly highly educated immigrants and allowed firms to expand, become more productive, and innovate. These positive effects on firms were particularly present in high-tech manufacturing, in skilled services, and among firms reporting a shortage of qualified workers in the mid-1990s. Our results highlight the role of computer technology driving the demand for skills and affecting the location decision of new immigrants, already prior to the reform.

5 Conclusion

Promoting the entry of foreign-born workers whose skills are in high demand in the national labor market is an important aspect of immigration policy in many countries. In the last decades, most developed countries experienced rapid growth in the demand for skills and an increase in wage inequality as a consequence of the widespread adoption of information and communication technology. Yet, there is no evidence informing policymakers of whether and how newly entering immigrants respond to these structural trends in the labor market and how immigration policies might affect

[40] Note that we instrument this interaction term with our instrument, as in Eq. (5), interacted with the policy indicator. This specification also includes the full set of origin-by-decade fixed effects absorbing the main effect of the policy, FMP_{st}.

this response. Previous research has focused on documenting the effects of ICT on skill-specific employment within the USA (Autor and Dorn 2013) and, separately, on how higher levels of inequality are correlated with the distribution of college-educated immigrants across countries (Grogger and Hanson 2011).

Building on these insights, this paper provides comprehensive evidence of how newly entering immigrants respond to these ICT-induced changes in economic opportunities and to which degree immigration policies modify this response. Our focus is on Switzerland, which experienced a boom in high-skilled immigration between 1990 and 2010. We exploit that different local labor markets, where new immigrants settle, were differentially exposed to ICT due to their pre-existing industrial specialization in routine task-intensive occupations.

First, we document the effects of ICT exposure on the economic opportunities of workers endowed with different skills. Paralleling the experience in the USA, we find regions with initial routine specialization experienced stronger growth in employment and relative wages at the top of the wage distribution compared to the middle. Different from the US context, however, we cannot reject the hypothesis that wages and employment did not change differentially for workers in the middle compared to those at the bottom of the wage distribution. Second, we present evidence that the skill mix of newly settling immigrants strongly responded to these changes in local economic opportunities. In particular, we find that regions with higher routine specialization attract stronger inflows of immigrants with a college education while the inflow of immigrants with an intermediate, secondary education was much weaker between 1990 and 2010. This effect is economically meaningful: on average across decades, ICT increased the relative number of high to middle educated among new arrivals by roughly 14% for a 5% difference in routine specialization (roughly the interquartile range across regions). In contrast, and also consistent with the insignificant change in relative economic opportunities at the bottom of the wage distribution, there is no differential inflow of middle-educated relative to low-educated foreign-born. These findings are robust to a large set of alternative explanations and sensitivity checks. These effects are considerably more pronounced in the service compared to the manufacturing sector. This evidence is strongly consistent with the hypothesis that newly entering immigrants are a selected group of individuals in strong pursuit of economic opportunities. Third, we exploit that Switzerland implemented the free movement policy after 2002 which gradually abolished all immigration restrictions for EU citizens but not for those from other countries. We find that the policy increased the total inflow of immigrants from EU countries (relative to those from other countries) but did not affect the relative size of different education groups at the national level. Contrary to fears expressed in the public debate, the opening of borders did not lead to a massive influx of lower educated immigrants nor did it lower the response of immigrants to skill-demand. If anything, it allowed regions with strong ICT-induced demand for skills to attract even larger numbers of highly educated foreign workers.

Our findings highlight the role of newly arriving immigrants as an important and previously undocumented channel of local adjustment to long-run ICT-induced structural change. To which degree this flexible supply of foreign-born talent allows reducing the economic inequality due to ICT is an important topic for future research.

Appendix

All appendix material (including tables and figures denoted with alphabetic letters) can be found in the GLO online paper version Beerli et al. (2021).

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Declarations

Conflict of interest The authors declare no competing interests.

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