# Returns to ICT Skills

Oliver Falck[a], Alexandra Heimisch-Roecker[b], Simon Wiederhold[c]

## Abstract

How important is mastering information and communication technology (ICT) on modern labor markets? We answer this question with unique data on ICT skills tested in 19 countries. Our two instrumental-variable models exploit technologically induced variation in broadband Internet availability that gives rise to variation in ICT skills across countries and German municipalities. We find statistically and economically significant returns to ICT skills. For instance, an increase in ICT skills similar to the gap between an average-performing and a top-performing country raises earnings by about 8 percent. One mechanism driving positive returns is selection into occupations with high abstract task content.

Keywords: ICT skills; broadband; earnings; international comparisons

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[a] LMU Munich, ifo Institute Munich, and CESifo Munich; postal address: Poschingerstraße 5, 81679 Munich, Germany; email: falck@ifo.de

[b] ifo Institute Munich; postal address: Poschingerstraße 5, 81679 Munich, Germany

[c] Corresponding author. KU Eichstaett-Ingolstadt, KU Research Institute BESH, ifo Institute Munich, CESifo Munich, and ROA Maastricht; postal address: Auf der Schanz 49, 85049 Ingolstadt, Germany; email: simon.wiederhold@ku.de

## 1. Introduction

"The new literacy" is the term Neelie Kroes, former Vice President of the European Commission, uses to describe an individual's skill in mastering information and communication technologies (ICT). She justifies this terminology by arguing that "the online world is becoming a bigger part of everything we do. No wonder these [ICT] skills are becoming central in the job market."[1] Neelie Kroes argues from an individual perspective: the increasing use of ICT alters skill requirements by being complementary to some skills and substitutable to others, and consequently changes the labor-market prospects of individuals depending on their skill portfolio. From a macro-perspective, the increasing use of ICT is transforming innovation activities and production. Thus, there is reason to suspect that a country's growth prospects are becoming increasingly dependent on its population's skills to master new technologies.[2] While earlier work has shown that ICT adoption has a positive effect on economic growth in a cross-country setting (most notably, Czernich et al., 2011 for broadband Internet), there is no convincing empirical evidence on the labor-market effects of ICT skills at the individual level. Using novel, internationally comparable skill data from the Programme for the International Assessment of Adult Competencies (PIAAC) across 19 countries, this paper provides the first systematic assessment of the wage returns to ICT skills.

To obtain the wage effect of ICT skills, we estimate a Mincer earnings function (Mincer, 1970, 1974; for an application with PIAAC data, see Hanushek et al., 2015) that relates a person's wages to that's person's education (proxied by the level of skills) and experience (proxied by a quadratic polynomial in age to capture non-linearities in the tenure-earnings relationship). However, estimating the wage effect of a specific skill domain, such as ICT skills, in the Mincerian framework is rendered difficult by the fact that it is unknown whether a person's level of ICT skills is simply a reflection of general ability. Notably, the seminal work by DiNardo and Pischke (1997) demonstrates that positive wage effects can also be found for pencil use at work, which are similar in magnitude to those of

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[1] http://www.getonlineweek.eu/vice-president-neelie-kroes-says-digital-literacy-and-e-skills-are-the-new-literacy/; accessed June 23, 2020.

[2] For instance, in endogenous growth models (e.g., Aghion and Howitt, 1992, 1998; Romer, 1990) innovation arises from intentional investments in research and development. This process is fundamentally guided by the underlying invention of people, which flows from the knowledge and skills of the population. Relatedly, in technological diffusion models, the rate at which economies can absorb the technological developments that happen outside depends again on the knowledge and skills of its population (e.g., Benhabib and Spiegel, 2005; Nelson and Phelps, 1966; Welch, 1970). As technological change is becoming more digital in nature (e.g., see recent developments such as the Internet of Things, Big Data, and Artificial Intelligence), individual's ICT skills are likely to assume a more prominent role for the generation and diffusion of new (digital) technologies in the future.

computer use. Based on this finding, they conclude that returns to computer use at work must be biased by unobserved skills of the users. Thus, drawing credible inferences on the wage effect of ICT skills requires exogenous variation in this specific skill domain.

Our identification strategy is based on the idea that ICT skills are developed by performing ICT-related tasks, which is facilitated by Internet access.[3] We implement two instrumental-variable (IV) strategies that exploit technologically induced variation in Internet availability across countries and across small geographical areas within a single country. In the cross-country strategy, this variation stems from international differences in the rollout of preexisting fixed-line voice-telephony networks that determine the timing of introduction and diffusion of high-speed Internet via broadband. These networks affect only the supply side of broadband diffusion in a country and therefore rule out demand-side effects based on differences in wealth and broadband-deployment policies (Czernich et al., 2011). To address the concern that richer and more productive countries have more extensive fixed-line networks as well as higher wages and more skilled workers, we exploit the pronounced age pattern in the impact of exogenous broadband availability on ICT skills. The youngest cohorts in PIAAC were toddlers when broadband emerged; the oldest cohorts were already reluctant to use the new technology. This allows us to identify returns to ICT skills based on differences in ICT skills and wages between age cohorts within countries.

In the second IV strategy, we exploit technological peculiarities that led to variation in broadband availability at a very fine regional level within Germany. Specifically, in the western part of Germany, the voice-telephony network was designed in the 1960s with the goal of providing universal telephone service to German households. In traditional telephone networks, the distance between a household and the main network node ("last mile") was irrelevant for the quality of voice-telephony services; however, about 40 years later, the last-mile distance restricted the availability of broadband Internet. Beyond a certain distance threshold, high-speed Internet access was not feasible without major infrastructure investment, a situation that excluded a considerable share of West German municipalities from early broadband Internet access (Falck et al., 2014).[4] We also control for the economic situation

[3] Recently, a stream of literature has emerged on the effects of Internet use on various (social) outcomes (see, e.g., Bauernschuster et al., 2014, for social interactions; Falck et al., 2014, for voting behavior; and Bhuller et al., 2013, for sex crimes). Moreover, Bulman and Fairlie (2016) provide an excellent overview of the impact of computer and Internet use on student achievement.

[4] Other studies have used variation in technological broadband availability across locations as a source of exogenous variation in actual use (e.g., Bertschek et al., 2013). However, this instrument is valid only conditional on structural location characteristics that determine the investment decisions of telecommunication carriers. Akerman et al. (2015) and Bhuller et

in a municipality before the emergence of broadband, which may be correlated with both baseline fixed-line networks and today's wages.

We find that the extent and technical peculiarities of the preexisting fixed-line infrastructure are significantly related to individuals' ICT skills, supporting the assertion that a higher (technologically determined) probability of having Internet access leads to learning-by-doing in ICT skills. Drawing only on variation in ICT skills attributable to exogenously determined broadband access, both IV strategies indicate a positive effect of ICT skills on wages that is economically and statistically significant. In the cross-country analysis, our ICT-skills estimate implies that if an average worker in the United States increased her ICT skills to the level of an average worker in Japan (i.e., the best-performing country in the skill assessment), her wages would increase by about 8 percent; this is close to the well-identified estimates on the returns to one additional year of schooling in developed countries. Thus, catching up in ICT skills from the middle of the international league table to the top position yields a similar wage increase as one additional year of schooling. In Germany, estimated returns to ICT skills are even somewhat larger. A detailed complier analysis suggests that returns to ICT skills for those who give rise to the identifying variation in the IV estimate are higher than for the average worker. One potential reason for this finding is that our IV approach isolates a specific dimension of ICT skills, namely, Internet skills, which were likely scarcer than overall ICT skills (which also include computer proficiency) when broadband emerged and therefore more highly rewarded.

We provide a comprehensive assessment of the validity of our identification strategy. For instance, we make use of the unique feature of our data that we not only have information on ICT skills but also on other skill domains, namely, numeracy and literacy. We can show in Placebo tests that our instruments are unrelated to these other skill domains when conditioning on ICT skills. We also show that the residualized (i.e., net of ICT skills) numeracy and literacy skills have high wage returns, suggesting that our IV approach isolates ICT skills from the part of numeracy and literacy skills most relevant for labor-market success.[5] Moreover, we carefully assess the exclusion restriction of our IV

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al. (2013) exploit variation in the timing of broadband deployment across locations in Norway, with the variation in timing stemming from limited funding of a public program and not due to decisions made by profit-maximizing telecommunication carriers.

[5] Our result that exogenous Internet availability affects only a specific set of skills is in line with Malamud and Pop-Eleches (2011). Exploiting an income threshold for eligibility for a computer voucher in Romania, they show that home computer ownership has zero or even negative effects on student achievement in math and reading but supports the development of ICT-related skills. Likewise, Faber et al. (2015) use a boundary-discontinuities strategy in the United Kingdom that relies on a similar idea as our within-Germany model, and find that the availability of fast Internet at students' homes has no effect on their test scores.

approach that exogenous broadband availability affects today's wages only through individuals' ICT skills, and not directly in any other way. In fact, our results continue to hold if we control for direct productivity effects of broadband within countries, industries, and even within detailed country-industry cells. Results are also robust to extensively controlling for initial cross-country differences in general technology affinity, spread of ICT-related industries, and economic strength.

A unique feature of the PIAAC survey is that it combines individual-level information on ICT skills, wages, and detailed occupation in a single dataset. This allows us to shed light on a potential mechanism behind the positive returns to ICT skills, namely, that the proliferation of personal computers caused a shift away from routine tasks—that is, those more amenable to automation—toward problem-solving and complex communication tasks (typically called "nonroutine abstract tasks"). This argument was first made by Autor et al. (2003) when developing their task-based approach to skill-biased technological change.[6] We expect that the complementarity of computers (requiring ICT skills) and abstract tasks allows workers with high ICT skills to select into abstract jobs and to benefit from the wage premia these jobs pay. To test whether occupational selection is an avenue through which ICT skills lead to higher wages, we estimate our IV models with abstract, routine, and manual task content as outcomes. We find that higher ICT skills increase the abstract task content of jobs and decrease their routine and manual task content. Back-of-the envelope calculations suggest that occupational selection explains about two-thirds of the wage increase caused by higher ICT skills.[7]

The paper is organized as follows. Section 2 describes the PIAAC data and the assessment of ICT skills. Section 3 outlines our two IV strategies. Section 4 presents the returns-to-ICT-skills estimates. Section 5 provides an analysis of the validity of our instruments. Section 6 investigates whether occupational selection explains positive returns to ICT skills. Section 7 concludes and derives implications for policy-making.

[6] See also Akerman et al. (2015), Autor and Dorn (2013), Autor et al. (2006, 2008), Black and Spitz-Oener (2010), Cortes (2016), Firpo et al. (2011), Goos and Manning (2007), Goos et al. (2014), Spitz-Oener (2006, 2008), and related earlier work by Acemoglu (1998) and Bresnahan et al. (2002). Acemoglu and Autor (2011) as well as Autor (2015) provide recent reviews of this literature.

[7] These results are in line with Gaggl and Wright (2017), who provide evidence for the United Kingdom that ICT investments increase the earnings and employment of workers engaged in abstract tasks. See also Akerman et al. (2015) for a task-based explanation of labor-market effects of broadband Internet adoption in Norway.

## 2. ICT Skills

Previous work on the wage returns to computer skills (see Draca et al., 2007, for a recent review) typically relied on self-reported measures of computer *use*, for instance, from the U.S. Current Population Survey (e.g., Krueger, 1993) or the British National Child Development Study (Dolton and Makepeace, 2004), implicitly assuming that workers with better skills are allocated to jobs in which computer skills are required. A few papers use self-reported measures of computer *knowledge* or *skills*, provided, for instance, in the German Qualification and Career Survey (e.g., DiNardo and Pischke, 1997) or in the British Skills Survey (e.g., Borghans and ter Weel, 2004).[8] Still, these measures are imperfect proxies for a worker's true skills because they are very crude, typically limiting answers to only a few categories,[9] suffer from reporting bias, and assume that workers are aware of the full skill distribution in the population. Moreover, existing worker surveys are not harmonized across countries, making an international analysis impossible. Furthermore, the returns from one or two decades ago may no longer be good indicators of the situation in economies that have undergone substantial technological change (discussed in, e.g., Acemoglu and Autor, 2011; Autor et al., 2003; Goldin and Katz, 2008).

One of the core features of this paper is its use of new and consistent international assessment data on the ICT skills of the adult population. These data come from the Programme for the International Assessment of Adult Competencies (PIAAC). PIAAC is the product of collaboration between participating countries through the Organization for Economic Co-operation and Development (OECD), and made use of leading international expertise to develop valid comparisons of skills across countries and cultures. The survey was conducted between August 2011 and March 2012 in 24 countries, which together represent about 75 percent of worldwide GDP.[10] PIAAC was designed to provide representative measures of the cognitive skills possessed by adults aged 16 to 65 years, and had

[8] A very recent example for the usage of self-reported computer skills is the study by Fairlie and Bahr (2017). They follow community-college students from disadvantaged backgrounds who were randomly assigned computers in 2006 for seven years. Their results indicate no effect of computer skills on earnings for these early-career workers.

[9] For instance, in the British Skills Survey, people were asked whether they have "simple," "moderate," "complex," or "advanced" computer skills.

[10] The countries that participated in PIAAC are Australia, Austria, Belgium (Flanders), Canada, Cyprus, the Czech Republic, Denmark, Estonia, Finland, France, Germany, Ireland, Italy, Japan, Korea, the Netherlands, Norway, Poland, the Russian Federation, the Slovak Republic, Spain, Sweden, the United Kingdom (England and Northern Ireland), and the United States. Canada (November 2011 to June 2012) and France (September to November 2012) were the only countries with a different survey period.

at least 5,000 participants in each country. The countries used different schemes for drawing their samples, but these were all aligned to known population counts with post-sampling weightings.[11]

Along with information on cognitive skills, PIAAC also offers extensive information on respondents' individual and workplace characteristics, for instance, hourly wages as well as skill use at home and at work. This information is derived from a detailed background questionnaire completed by the PIAAC respondents prior to the skills assessment. The survey was administered by trained interviewers either in the respondent's home or at a location agreed upon between the respondent and interviewer.[12]

PIAAC provides measures of cognitive skills in three domains: literacy, numeracy, and ICT (called "problem solving in technology-rich environments" in the survey). PIAAC measures each of the skill domains on a 500-point scale.[13] The individual-level correlation of ICT skills with literacy (numeracy) is 0.78 (0.73), which is less strong than the correlation between numeracy and literacy (0.82). Nevertheless, all three skill domains appear to measure distinct dimensions of a respondent's skill set.[14]

We focus on ICT skills, defined as "using digital technology, communication tools and networks to acquire and evaluate information, communicate with others and perform practical tasks" (OECD, 2013, p. 86).[15] To assess ICT skills, participants were given a series of problem scenarios and asked to find solutions to them using ICT-based applications such as an Internet browser and web pages, e-mail, word processing, and spreadsheet tools. The OECD does not publish the problem sets that were actually included in the assessment, but gives examples of tasks similar to those that were used in the

[11] After the main PIAAC study was conducted in 2011/2012, there were two additional rounds of the PIAAC test. In 2014/2015, the second round of PIAAC was conducted in nine countries; in 2017/2018, further six countries participated in the third and final round of PIAAC. Our study uses only data from the first round of PIAAC.

[12] The PIAAC Public Use File reports hourly wages for Austria, Canada, Germany, Sweden, and the United States only as a worker's decile rank in the country-specific wage distribution. For Germany, we obtained the Scientific Use File, which contains continuous wage information. For the remaining countries, we follow Hanushek et al. (2015) in assigning the decile median of hourly wages to each survey participant belonging to the respective decile of the country-specific wage distribution. Moreover, in each country, we trim the bottom and top 1 percent of the wage distribution to limit the influence of outliers. Our results are not sensitive to whether or not we trim wages.

[13] PIAAC provides 10 plausible values for each respondent and each skill domain. Throughout, we use the first plausible value of the PIAAC scores in each domain. See Perry et al. (2014) for a discussion of the plausible values in PIAAC.

[14] The International Adult Literacy Survey (IALS), the predecessor of PIAAC, suffered from pair-wise correlations of individual skill domains that exceeded 0.9, making it virtually impossible to distinguish between different skills. Moreover, ICT skills were not assessed in IALS.

[15] Literacy is the ability to understand, evaluate, use, and engage with written texts so as to participate in society, achieve one's goals, and develop one's knowledge and potential. Numeracy is the ability to access, use, interpret, and communicate mathematical information and ideas in order to engage in and manage the mathematical demands of a range of situations in adult life. See OECD (2013) for details.

test. For instance, one task was to click through a number of different websites containing calls for jobs and to bookmark all websites which do not require to register or to pay a fee. Accordingly, this task involves maneuvering between websites, processing of information, and a basic understanding of web browsers. Special software was programmed for the ICT skills assessment, to make sure that person who are not familiar with a specific software (e.g., Microsoft Excel or Word) do not have a disadvantage.

Often, solving the tasks in the ICT skills assessment required a combination of several applications, for example, managing requests to reserve a meeting room using a web-based reservation system and sending out e-mails to decline reservation requests that could not be accommodated.[16] In general, ICT skills as assessed in PIAAC measure the extent to which a participant is capable of using modern information and communication tools to get along in a digital world. PIAAC's ICT test does not reflect proficiency in more specific computer skills like advanced programming. However, the rather basic ICT skills tested in PIAAC likely provide the foundation for developing more complex ICT skills; for instance, occupations which likely require most advanced ICT skills (i.e., software developers, programmers, database designers) also score highest in PIAAC's ICT test. Problem solving using modern information and communication tools certainly also involves literacy and numeracy skills, which explains the rather strong correlation with literacy and numeracy skills reported above.

ICT skills were assessed in a computer-based mode, so some basic knowledge regarding the use of computers was required to even participate in the ICT skill test; 7.5 percent of all PIAAC participants indicated in the background questionnaire that they had no prior computer experience and thus these participants did not take part in the computer-based assessment. Instead, they took the survey via pencil and paper, and only their numeracy and literacy skills were tested. Participants who reported at least basic knowledge of computer-based applications were issued an ICT core test, which assessed basic ICT competencies such as using a keyboard/mouse or scrolling through text on the screen; 5.1 percent of all participants did not pass this test and were excluded from the ICT skills assessment. Moreover, 9.8 percent of all participants opted to take the paper-based assessment without first taking the ICT

[16] See OECD (2013, p. 89, 2015, p. 39f.) for other examples of problem scenarios used in PIAAC to test participants' ICT skills. The ICT tasks to be solved were of three levels of difficulty.

core assessment, even though they reported some prior experience with computers.[17] Persons without an ICT skills score are excluded from our main estimation sample.[18]

Assessing ICT skills was an international option. Cyprus, France, Italy, and Spain did not take part in the ICT skills assessment, which leaves us with data for 19 countries.[19] We also drop individuals aged 16–19 years because most have not finished their education. Moreover, our identification strategy (see Section 3) requires that we can ascribe respondents' ICT skills to broadband Internet access in the PIAAC test country. We therefore exclude first-generation immigrants, who often have developed their ICT skills in a country other than the PIAAC test country.[20] The resulting sample includes 53,879 individual-level observations.[21]

Figure 1 depicts ICT skills by country, showing mean, median, and interquartile range of the ICT skills distribution. The average (median) level of ICT skill across PIAAC countries is 287 points (289 points), with a standard deviation (SD) of 41 points.[22] Respondents in Japan, Sweden, Australia, and the Netherlands have the highest average scores; respondents in the former communist countries (the Czech Republic, Estonia, Poland, and the Slovak Republic) and Ireland score lowest. The difference between Japan (the best-performing country with 299 points) and Poland (the worst-performing

[17] Not surprisingly, people who took the paper-based assessment are, on average, older than people who took the computer-based assessment, regardless of the reason for this choice (i.e., no computer experience, failed in core ICT test, opting out). People whose skills were assessed via the paper-based format also tend to use the Internet and computers very infrequently, if at all, at home. Moreover, they have, on average, lower numeracy and literacy skills. See also Rammstedt (2013) and OECD (2015).

[18] The fact that ICT skills could not be tested for all respondents implies sample selectivity. To check whether this matters for our results, we assign people with missing ICT skills a very low value of ICT skills (e.g., zero ICT skills; minimum ICT skills either of all respondents or of the respondents in the same country; one percent of the median observed ICT skills in a country). We also experimented with other imputation methods. Returns to ICT skills tend to increase in these more inclusive samples, which is hardly surprising given that people without ICT skills information often work in low-paying jobs (see above). See Online Appendix D for details.

[19] We also exclude the Russian Federation from the analysis. According to OECD (2013), data for the Russian Federation are preliminary, may still be subject to change, and are not representative of the entire Russian population because they do not include the population of the Moscow municipal area.

[20] Placebo tests and robustness analyses (see Online Appendices C and D) show the appropriateness of these sample restrictions.

[21] The international PIAAC sample with 24 countries contains 164,997 observations. Without the four countries that opted out of the ICT skills assessment and the Russian Federation, sample size is 138,383 observations. ICT skills could not be measured for 32,831 individuals. We restrict the sample to persons who are employed at the time of the PIAAC survey, trim the bottom and top 1 percent of the wage distribution, and exclude self-employed who do not report hourly wage information in PIAAC, leading to a decrease in sample size by 41,549 observations. The age restriction further reduces the sample by 2,989 workers and dropping first-generation immigrants reduces it by 6,349 workers. Finally, we exclude 786 workers with missing information on migration status, gender, education, full-time status, or work experience, resulting in a sample of 53,879 workers.

[22] Both mean and SD of numeracy and literacy skills are very similar in the international sample (see Table A-1).

country with 273 points) amounts to roughly 0.6 SD. Countries also differ in how ICT skills are distributed in the population. The ICT skill distribution is widest in Poland, the United States, and the Czech Republic, where the 25th–75th percentile skill range amounts to more than 60 points, and is most compressed in Korea, with an interquartile range of less than 50 points.

Figure A-1 in Online Appendix A shows that ICT skills tend to decrease by age (298 points for age group 20–34 vs. 267 points for age group 55–65). Similarly, tertiary-educated workers outperform workers with below-tertiary education, but not by a large margin (301 points vs. 277 points). However, there is substantial variation in ICT skills for all age ranges and education levels. The wide variation in ICT skills even within the groups of young adults or college-educated workers suggests that ICT skills are tolerably difficult to acquire, so having them might be rewarded by employers. The idea that ICT skills cannot easily be acquired is further supported by the fact that about 24 percent of the population do not possess even very basic ICT proficiency (see above).

Table A-1 in Online Appendix A sets out descriptive statistics of participants' characteristics for the pooled international sample and separately for each country. The size of the estimation sample ranges from 1,649 persons in the Slovak Republic to 10,499 persons in Canada. The Canadian sample is much larger than that of any other PIAAC country due to oversampling to obtain regionally reliable estimates. Also apparent from Table A-1 are the substantial differences in hourly wages (in PPP-USD) across countries. Workers in Norway, Denmark, and Ireland earn the highest wages and workers in the post-communist countries are paid the least, with the difference between the highest-paying country (Norway) and lowest-paying country (the Slovak Republic) amounting to 1.6 SD.

In the econometric analysis, we standardize ICT skills to have mean zero and SD one[23] and always employ the sample weights provided in PIAAC.[24]

[23] In the international analysis, we standardize scores using the cross-country SD; in the German analysis, we use the within-Germany SD. Both are almost exactly at 41 PIAAC points.

[24] In the cross-country analysis, we restrict the sum of all individual-level weights within a country to equal one to account for differences in sample size across countries; we employ an analogous weight adjustment that restricts the sum of all individual-level weights within a municipality to equal one in the within-Germany analysis.

## 3. Identification Strategy

### *3.1 Empirical Model*

We estimate returns to ICT skills in a general Mincer framework (Mincer, 1970, 1974) that relates a person's human capital to earnings on the labor market. Specifically, the international analysis is based on the following individual-level wage regression:

$$\log w_{ic} = \beta_0 + \beta_1 ICT_{ic} + \boldsymbol{X_{ic}\beta_2} + \mu_c + \varepsilon_{ic}. \qquad (1)$$

$w_{ic}$ is gross hourly wages earned by individual $i$ living in country $c$ and $ICT_{ic}$ are the individual's ICT skills. $\boldsymbol{X_{ic}}$ is a vector of individual-level variables including age and gender. Following Hanushek et al. (2015), we estimate an earnings function without years of schooling, which is one of several inputs into cognitive skills. $\mu_c$ are country fixed effects that account for any differences in the countries' wage levels. $\varepsilon_{ic}$ is a standard error term. The coefficient of interest is $\beta_1$, which shows the wage change in percent when ICT skills increase by one SD.[25]

In this basic regression framework, $\beta_1$ can hardly be interpreted as the causal effect of ICT skills on wages. The most obvious reasons for $\beta_1$ being a biased estimate of the true returns to ICT skills are measurement error, reverse causality, and omitted variables (for a discussion, see Hanushek et al., 2015). Measurement error may occur if cognitive skills in PIAAC are just an error-ridden measure of the human capital relevant on the labor market. For instance, since the ICT-based applications included in the PIAAC test are unfamiliar to the respondents, they may have problems solving the tasks even if they are perfectly capable of using ICT at their workplace. Errors in the measurement of ICT skills can also occur if PIAAC respondents had a bad testing day or solved tasks correctly or incorrectly simply by chance. This measurement error in the assessment of an individual's ICT skills will bias the coefficient on ICT skills toward zero. Moreover, higher earnings may actually lead to improvements in ICT skills, giving rise to the problem of reverse causality. Better jobs may more likely require and reinforce skills or they may provide the resources to invest in adult education, training, or computer courses. Reverse causality will likely lead to an upward bias of the returns-to-ICT-skills estimates. Finally, omitted-variable bias may arise because unobserved variables like non-cognitive skills, personality traits, or family background could directly influence earnings and may also be related to ICT skills. The direction of the

[25] For ease of exposition, we frequently refer to $\beta_1$ simply as the "return to ICT skill." It does not, however, correspond to a rate of return calculation because we have no indication of the cost of achieving any given level of skill. See also Heckman et al. (2006).

omitted-variable bias is not clear a priori. For instance, Malamud and Pop-Eleches (2011) find that home computers increase computer knowledge but worsen grades, implying that ICT skills may be negatively related to other skills. This would bias the least squares estimates downward. A positive correlation of ICT skills with other unobserved variables that are valued on the labor market would bias the least squares estimates upward.

To solve these endogeneity problems, we employ two IV strategies. The basic idea behind both is that individuals acquire ICT skills through learning-by-doing, and that this learning is facilitated when there is access to broadband Internet. Specifically, we exploit technologically determined variation in the availability of broadband Internet access via DSL across countries and between highly disaggregated regions within a single country. These IV models can be interpreted as a reduced form of the following three-stage model: (1) technological peculiarities of the broadband technology predict broadband diffusion; (2) broadband diffusion predicts ICT skills; and (3) ICT skills determine wages.

### *3.2 Characteristics of the DSL Network*

DSL, one of the two dominant fixed-line broadband Internet access technologies worldwide,[26] relies on the copper wires of the voice-telephony network connecting households with the main distribution frame (MDF). The voice-telephony networks were typically planned and rolled out by state monopolies, so decisions concerning infrastructure deployment were usually made on the basis of political rather than commercial considerations. Many countries implemented a universal service obligation, forcing telecommunication carriers to provide their services at affordable prices regardless of households' geographic location.

The copper wires—which were solely used for fixed-line voice calls before the emergence of DSL technology—could be upgraded to provide DSL by installing new hardware (so called DSLAMs) at the MDFs, making data traffic at high bandwidths to the telecommunication carrier's backbone network feasible (see Figure A-2). This technological feature of DSL technology made broadband rollout substantially cheaper compared to having to roll out new wires to households. Even in countries where fiber was rolled out to the curbs or homes, the existing ducts of traditional fixed-line networks were used to reduce the deployment cost of broadband. Thus, the existing fixed-line infrastructure initially built for purposes other than the provision of broadband allowed for an economically viable widespread

[26] The major alternative fixed-line access technology is broadband access via cable TV networks (see Section II of Online Appendix C).

diffusion of broadband Internet (Czernich et al., 2011). In consequence, countries with a high fixed-line penetration before the introduction of DSL could roll out broadband earlier and reached a larger share of the population faster than countries lagging behind in fixed-line infrastructure (see Section 3.3).

At the same time, the reliance of broadband rollout on traditional voice-telephony networks led to an uneven distribution of broadband access within countries in the early years of the Internet era. While the distance between the household and the MDF, the so-called last mile (see Figure A-2), is irrelevant for the quality of voice-telephony services, it determines the feasibility of DSL technology and therefore plays a crucial role in broadband access. Above a certain last-mile distance, DSL is no longer feasible without major infrastructure investment. This technological peculiarity of DSL technology induces exogenous variation in broadband access at a very fine regional level (see Section 3.4).

### *3.3 Cross-Country Instrumental-Variable Model*

We begin by showing that preexisting fixed-line infrastructure affected the introduction and initial diffusion of broadband Internet. Figure 2 reveals a negative relationship between a country's fixed-line infrastructure in 1996 (broadband first emerged in Canada in 1997) and the year broadband was introduced in the country. Similarly, Figure 3 shows a strong positive relationship between preexisting fixed-line diffusion and broadband diffusion in 2006, that is, several years after the first introduction of broadband. Both figures indicate that broadband infrastructure relies on traditional fixed-line networks.

One may wonder why the extent of fixed-line networks differed at the advent of DSL diffusion. As was already noted, a country's fixed-line penetration was largely determined by the degree to which the universal service obligation was implemented. Implementation differed across countries along three dimensions: availability, affordability, and accessibility (e.g., for people with disability) (see OECD, 2006, for an overview). With respect to the geographic extent of the voice-telephony network, the first dimension is of importance only. Consequently, those countries that put emphasis on availability had farther reaching voice-telephony networks than countries that put more emphasis on the other two dimensions. For instance, in the U.K. the universal service obligation requires British Telecom (and Kingston Communications in Hull) to provide a connection to the fixed-line network at a uniform price to basically everybody. By contrast, in the U.S., the universal service obligation focuses on affordability (discounts to low-income consumers and financial support to companies in high-roll-out-cost areas) and accessibility (for schools, libraries, and rural health care centers). These differences in implementation between the U.K. and the U.S. can also be seen in Figure 3. Even after controlling for country-level characteristics, the U.K. had a farther reaching voice-telephony network in 1996 than the U.S.

However, the reliance of broadband Internet diffusion on preexisting fixed-line networks became substantially weaker over time. In fact, broadband diffusion in 2012 (i.e., the year of the PIAAC survey) is not significantly related to initial fixed-line diffusion (orange line in Figure 3). One reason cross-country differences in broadband penetration tend to flatten out over time is the S-shaped diffusion pattern of new technologies (Geroski, 2000; Griliches, 1957): countries that adopted broadband Internet earlier reach the concave part of the diffusion curve sooner, and thus broadband penetration grows more slowly than in countries that introduced broadband later. Moreover, new technologies such as mobile broadband infrastructure attenuate the importance of DSL for accessing the Internet.[27]

The variation in broadband Internet availability that we draw on to explain ICT skills thus mainly comes from the early years of the Internet era. One question that naturally arises is to what extent broadband Internet in these early years provided added value to consumers compared to technologies already available. Before the introduction of broadband Internet, only low-speed Internet access via dial-up-type technologies such as modems and ISDN was feasible. Even in the best case of high-end ISDN access, the maximum available speed was 128 kbit/s. The bandwidth increased substantially with the emergence of broadband, reducing limitations to Internet use as well as the excessive waiting times for loading web pages. According to a study by the Pew Internet and American Life Project (2002), even simple activities such as writing an e-mail are carried out more often when broadband access instead of dial-up technology is available in a household (52 vs. 67 percent). The advantage of fast Internet access is even more pronounced for information-seeking activities (13 vs. 30 percent), also including job-related research (14 vs. 36 percent). We therefore expect that primarily the availability of broadband Internet (vis-à-vis Internet access via dial-up technology) induces learning-by-doing effects in the accumulation of ICT skills. Note, however, that Internet use beyond the mere consumption of content (e.g., podcasting, blogging, social networking), as prevalent the second half of the 2000s, is less likely to contribute to the learning-by-doing effects we identify.

[27] For instance, according to the annual ICT survey conducted by the German Federal Statistical Office, the share of German firms that use mobile broadband technologies to access the Internet more than doubled between 2008 and 2012, from 14 percent to 33 percent. In contrast, the share of firms using DSL to connect to the Internet has held constant at 80 percent since 2008 (Federal Statistical Office, 2012). However, given that most firms rely on DSL to access the Internet and are therefore also affected if DSL is unavailable for technical reasons, our IV strategy is likely picking up learning-by-doing effects in the accumulation of ICT skills at work *and* at home.

The fact that our identifying variation stems from the early phase of broadband diffusion induces a distinct age pattern in the impact of technologically determined broadband availability on the ICT skills of PIAAC respondents, which we exploit in the cross-country analysis. Figure 4 plots the effect of fixed-line diffusion in 1996 (i.e., before the emergence of broadband Internet) on ICT skills by five-year age cohort in our international sample. The bars in Figure 4 can be interpreted as follows: in countries where the fixed-line network (telephone subscribers per inhabitant in 1996) covers the entire population (diffusion of 1), the ICT skills of, say, 20-24 year olds are about one SD higher than in countries where nobody has a telephone connection (diffusion of 0).[28] The horizontal axis of Figure 4 has two scales—the upper scale shows a person's age at the time of the PIAAC survey and the lower scale shows how old these persons were when broadband first emerged in 1997. Around that time, traditional fixed-line networks should have affected broadband availability most.

The figure reveals an inverted U-shaped age pattern in the effect of technologically determined broadband availability on ICT skills.[29] The young cohorts in the PIAAC sample (16–34 years) were toddlers or still at school when broadband Internet emerged in 1997 (see lower scale of horizontal axis), and thus were not using this technology professionally.[30] We observe the strongest impact of technologically induced broadband availability for PIAAC respondents aged 35–44 years, who entered the labor market or started university in the early years of the Internet era. This is consistent with the notion that the most prominent applications of the Internet in these years were writing e-mails and looking up information. The effect of early broadband availability diminishes for older ages, which is explained by the psychological literature stressing that older individuals suffer more often from computer anxiety and have less computer self-efficacy (Czaja et al., 2006).[31] Note that Figure 4 is very similar when adjusting ICT skills by the age-specific SD to avoid potential ceiling effects (results available upon request).

[28] However, the actual fixed-line diffusion in 1996 varied only between 0.17 (Poland) and 0.68 (Sweden).

[29] We also observe an inverted U-shaped age pattern in computer use when looking at data from the time use survey conducted by the German Federal Statistical Office. In 2001/2002, 13 percent of computer users were 10–17 years old, 21.4 percent were 18–29 years old, 15 percent were 30–44 years old, and only 4.4 percent were 45–64 years old.

[30] Many of the more leisure-oriented Internet applications (e.g., Facebook, YouTube, and Twitter) emerged only in the second half of the 2000s.

[31] In Figure A-3, we observe that in countries with higher exogenous broadband availability, older individuals less often report not having any experience with computers and are also less likely to opt out of the ICT assessment. This evidence suggests that being exposed to the Internet increases individuals' confidence in their computer and Internet abilities over time. We find no distinct age pattern in the effect of exogenous broadband availability on failing the ICT core test, indicating that by 2012, all countries were equally able to equip their inhabitants with very basic ICT skills.

Exploiting this pronounced age pattern in the impact of exogenous broadband availability on ICT skills, we estimate returns to ICT skills from differences in ICT skills and wages between age cohorts within countries. We implement the international IV model using two-stage least squares, where $ICT_{ic}$ in the second-stage model (see Equation (1)) is the predicted value of the following first-stage model:

$$ICT_{ic} = \alpha_0 + \sum_a \alpha_{1a} a_{ic} \times FD_c + \boldsymbol{X_{ic}\alpha_2} + \mu_c + \vartheta_{ic}. \tag{2}$$

Here, our instruments are interactions of the country-level fixed-line diffusion in 1996, $FD_c$ (which determined broadband availability in the early Internet period), with indicators for the age cohorts, $a_{ic}$. For expositional purposes, we aggregate the five-year age cohorts in PIAAC to broader age groups (i.e., 20–34, 35–44, 45–54, and 55–65 years), since Figure 4 indicates that the effect of fixed-line diffusion on ICT skills is rather similar within these age groups.[32] The vector $\boldsymbol{X_{ic}}$ contains the individual-level control variables from Equation (1) and $\mu_c$ are country fixed effects. Due to the inclusion of country fixed effects, the main effect of fixed-line diffusion (pertaining to the omitted age cohort, 55–65 years) on ICT skills (first stage) or wages (second stage) is not identified. $\vartheta_{ic}$ is the error term of the first-stage equation.

We report Huber-White heteroskedasticity-robust standard errors. We do not cluster standard errors because the variation we are using is at the individual level, that is, the variation comes from an individual's age (see also Angrist and Krueger, 1991, for a similar argument).[33] However, as can be seen from Table A-2, estimated returns to ICT skills remain statistically significant when we cluster standard errors at the country level (i.e., the level where fixed-line diffusion varies) or the country-times-age level, and are just shy of being significant (*p*-value of 0.106) when we cluster at the country times age-bracket level. The table also shows that results are similar when using the wild bootstrap procedure suggested by Cameron et al. (2008) for improved inference with few clusters (using Stata's *boottest* command for implementation).

The IV model in Equation (2) exploits the fact that the ICT skills of different age cohorts within each country benefit differently from early (exogenous) broadband access. Using only age-induced

[32] We also experimented with using quadratic, cubic, or quartic polynomials in age. However, none of these functional forms is flexible enough to capture the actual age pattern, as can be seen in Figure A-4.

[33] Assigning individuals to age *brackets* is mainly for illustrative purposes, and it allows us to more flexibly capture the age pattern in openness to broadband adoption than using a linear or quadratic polynomial in age.

variation within countries addresses two major concerns. First, it captures any direct positive economic effect of the traditional fixed-line infrastructure on current wage levels. In fact, Roeller and Waverman (2001) show that a significant portion of economic growth in OECD countries between 1971 and 1990 can be attributed to telecommunications. Second, it controls for a potential correlation of baseline fixed-line networks with baseline levels of wealth, technology, education, institutions, skills, and so forth, all of which may affect today's ICT skills and wages.

However, key to our identification strategy is that the effect of any omitted variables does not follow the same inverted-U-shaped age pattern as the effect of exogenous broadband availability does. This assumption may fail to hold if omitted variables affect younger and older workers differently. Thus, Sections 5.2 and 5.3 provide comprehensive evidence that our results cannot be attributed to country-cohort specific factors. We can even allow for differential age trends by country, which addresses the concern that productivity and wages of young workers may benefit disproportionally from broadband (e.g., Autor and Dorn, 2009).

### *3.4 Within-Germany Instrumental-Variable Model*

The extent of the preexisting fixed-line networks that we exploit for identification in the international IV strategy only affects the supply side of broadband diffusion and thus rules out demand-side effects based on differences in wealth as well as policy-induced effects. However, there may be concern that the age pattern in the uptake of broadband Internet is not fully exogenous but depends, at least to some degree, on the perceived labor-market benefits of using this new technology. We therefore complement the international analysis with a second IV strategy that uses regional variation within Germany in the deployment of broadband infrastructure as an instrument for ICT skills.

In general, differences in broadband diffusion across regions within a country are largely determined by the endogenous decisions of profit-maximizing telecommunication carriers, which are, in turn, influenced by demand factors such as income, education, and urbanization. Since these factors may also affect current wages, we exploit the fact that past a certain threshold in the distance between a household and its assigned MDF broadband is no longer feasible (see Section 3.2). Specifically, in West Germany, the general structure of the voice-telephony network dates back to the 1960s when the provision of telephone service was a state monopoly having the declared goal of providing universal telephone service to all German households.[34] While all households connected to an MDF enjoyed the same quality voice-telephony services, only those households closer than 4,200 meters (2.6 miles) to their assigned MDF could gain access to broadband Internet when a DSLAM was installed.[35] Past this threshold, DSL technology was no longer feasible without replacing parts of the copper wire (typically placed between the MDF and the street cabinet) with fiber wire (see Figure A-2). Since this replacement involved costly earthworks that increased with the length of the bypass, certain West German municipalities were excluded from early broadband Internet access.[36]

We follow Falck et al. (2014) in using the 4,200-meter threshold as a source of exogenous variation in the availability of DSL technology in a municipality. We calculate the distance of a municipality's geographic centroid (as a proxy for the location of the average household) to the assigned MDF and merge this information with the German PIAAC data. Following a line of argumentation similar to that in the cross-country identification strategy, we expect that PIAAC respondents in municipalities above the 4,200-meter threshold have lower ICT skills because they had less opportunity to accumulate ICT skills due to a lack of high-speed Internet access.

Over time, many countries expanded ICT infrastructure to their so-called white spots, which are predominantly rural municipalities that would remain underprovided if left to market forces. Today, most countries have achieved a basic provision of broadband Internet to almost all households. Figure 5 shows the share of households with access to DSL between 2005 and 2009 in municipalities below and above the 4,200-meter threshold.[37] According to the figure, about 30 percent of the initial difference

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[34] We ignore East Germany since we cannot rule out that location decisions for the MDFs in East Germany, which were made after Reunification in the 1990s, were partly determined by unobserved characteristics of the municipalities that are also correlated with individual wages (see Bauernschuster et al., 2014, for details). Berlin is also dropped from the analysis because we are unable to distinguish between former West and East Berlin in terms of DSL availability.

[35] The threshold value of 4,200 meters is a consequence of the DSL provision policy of the German telecommunication carrier, Deutsche Telekom, which marketed DSL subscriptions at the lowest downstream data transfer rate of 384 kbit/s only if the line loss was less than 55 decibel (dB). Since the copper cables connecting a household with the MDF usually had a diameter of 0.4 mm, a line loss of 55dB was typically reached at about 4,200 meters. As the actual line loss depends on other factors as well, the 4,200-meter threshold is only a fuzzy threshold (Falck et al., 2014). This fuzziness in the technological threshold of DSL availability is substantially more severe in other countries, effectively limiting the use of the threshold identification to Germany.

[36] The costs of rolling out one kilometer of fiber wire subsurface amount to €80,000, with an additional €10,000 to install a new node connecting the remaining part of the copper wires to the fiber wire (Falck et al., 2014).

[37] Availability of DSL is measured as the percentage of households in a municipality for which DSL is technologically feasible. Data are from the German Broadband Atlas, commissioned by the German Federal Ministry of Economics, in which telecommunication operators self-report the number of households covered by their networks at a minimum downstream data transfer rate of 384 kbit/s. Consistent data on DSL availability at the municipality level are available only for this short time period.

in DSL availability was eliminated after this four-year period. Similar to our cross-country specification, variation in broadband Internet availability thus mainly comes from the early years of the Internet era.

The first-stage model in the within-Germany analysis is a municipality-level $(m)$ version of Equation (2), using as instrument for ICT skills a dummy variable $(T)$ that indicates whether a municipality is more than 4,200 meters away from its assigned MDF:

$$ICT_{im} = \alpha_0 + \alpha_1 T_m + \boldsymbol{X_{im}\alpha_2} + \boldsymbol{X_m\alpha_3} + \vartheta_{im}. \tag{3}$$

The vector $\boldsymbol{X_{im}}$ includes a quadratic polynomial in work experience and gender.[38] Since we cannot include municipality fixed effects in this specification, the vector $\boldsymbol{X_m}$ contains controls for a municipality's economic situation prior to emergence of broadband by including municipality-level unemployment rate and the local age structure, both measured in 1999 (broadband first emerged in 2000 in Germany).[39] $\vartheta_{im}$ is the error term. As the threshold instrument varies only across municipalities, standard errors in the within-Germany analysis are clustered at the municipality level (Moulton, 1986, 1990).

In an extension, we focus on municipalities without an own MDF. Densely populated municipalities always have at least one own MDF and are typically below the 4,200-meter threshold; less agglomerated municipalities often share an MDF. The choice of MDF locations in these less-agglomerated areas was determined by the availability of lots and buildings for hosting an MDF at the time the voice-telephony network in Germany was planned, that is, in the 1960s. This sample thus includes only municipalities that were not chosen to host an MDF, which homogenizes the sample of municipalities with respect to socioeconomic characteristics. Some municipalities, however, were (arguably randomly) lucky to be close enough to an MDF in another municipality to have access to broadband Internet. This provides variation in the instrument in the restricted sample.[40] However,

[38] This specification follows the baseline model in Hanushek et al. (2015). In Online Appendix D, we report results when replacing work experience by age. Results are also similar when we use age cohort dummies as in the international analysis (results available upon request).

[39] Data come from the German Federal Statistical Office. The unemployment rate is calculated by dividing the number of unemployed individuals by the population aged 18 to 65 years. To account for territorial changes due to municipality reforms that took place between 1999 and 2012, we use population weights provided by the Federal Institute for Research on Building, Urban Affairs, and Spatial Development to recode the data in *ArcGIS*.

[40] In the full sample, 13 out of 204 municipalities (6.4%) are above the 4,200-meter threshold. In the sample of municipalities without an own MDF, half of the municipalities (9 out of 18) are above the threshold. This suggests that the identifying variation in the overall German sample mainly comes from sparsely populated, rural municipalities.

sample size is considerably smaller than in the full sample because the sampling of municipalities in PIAAC was proportional to municipality size (Rammstedt, 2013).

While it would in principle be possible to implement the age-cohort-based identification from the international analysis also in the German analysis, we refrain from doing so for three reasons: First, as we only have a limited number of observations within each municipality due to the sampling frame of PIAAC, municipalities often do not cover the full age range, so there is much less age variation within municipalities than within countries. Second, the age composition differs across municipalities, which is mainly due to selective mobility across municipalities. Third, the credibility of our results greatly benefits when they can be obtained from to identification strategies that use completely different sources of identifying variation (i.e., fine-grained regional variation in the German analysis and age variation in the international analysis).

## 4. Returns to ICT Skills

### *4.1 International Evidence*

We now estimate the causal effect of ICT skills on individuals' wages. Columns (3) and (4) of Table 1 present the results from our cross-country IV model. In the lower panel of Table 1, we report the first-stage coefficients as well as the Cragg-Donald F statistic on the excluded instruments and the associated critical values (Stock and Yogo, 2005). The instruments turn out to be strong predictors of ICT skills. In the specification with country fixed-effects serving as our baseline (Column (4)), the Cragg-Donald F statistic is 28.5 and thus well above the critical value of 9.1. Thus, weak instrument bias is not a worry in this context. The first-stage estimates indicate a distinct age pattern in the effect of exogenous broadband availability on ICT skills. Compared to the effect for persons aged 55–65 years (the omitted category), an increase in the voice-telephony penetration rate from 0 to 100 percent leads to a 0.38 SD larger increase in the ICT skills of 20–34 year olds, a 0.84 SD larger increase for 35–44 year olds, and a 0.25 SD (albeit insignificantly) larger increase for 45–54 year olds.[41]

The upper panel of Table 1 shows the corresponding second-stage results. Across specifications, our results indicate significant returns to ICT skills. In our baseline specification in Column (4), the ICT skill coefficient of 0.236 implies that a one SD increase in ICT skills attributable to a historically larger fixed-line network leads to a 23.6 percent increase in wages. Returns are very similar when we leave out

[41] Complete first-stage results can be found in Table A-3.

country fixed effects and instead include the main effect of fixed-line diffusion to capture omitted variables that are correlated with ICT skills in the same way for all age groups within a country (Column (3)).

For assessing the magnitude of the estimated effect, note that one SD in ICT skills is substantial. The difference in average ICT skills between the best-performing and worst-performing country is only 0.6 SD (see Table A-1). Likewise, one SD in ICT skills is roughly twice the learning progress made by school-attending PIAAC respondents between lower secondary and upper secondary education, which amounts to 20 PIAAC points across the countries participating in the study.[42] We therefore provide some alternative interpretations of our effect size. For instance, if an average worker in the United States (with ICT skills of 285 points) increased her ICT skills to the level of an average worker in Japan (299 points), her wage would increase by about 8 percent; this is close to the well-identified estimates on the returns to one additional year of schooling in developed countries (e.g., Card, 1999; Heckman et al., 2006). Prime-age workers (aged 35–54 years) would experience a similar wage increase of about 8 percent if they could boost their ICT skills to the level of entry-age workers (aged 20–34 years). Another way to interpret our ICT-skills estimate is to consider occupational differences in ICT skills. Not surprisingly, ICT professionals (e.g., software developers, programmers, database designers) have by far the highest ICT skills across all occupations. They outperform the next-best occupation (ICT technicians) by 12 points (equivalent 0.29 SD) and are 36 points (equivalent to 0.87 SD) above the average in ICT skills. Our results imply that a worker with average ICT skills would increase her wage by 20 percent if she could bring her ICT skills to the level of ICT professionals.

It is also useful to compare the returns to ICT skills with existing estimates on returns to cognitive skills in other domains. In their sample of prime-age, full-time employed workers, Hanushek et al. (2015) find returns of 17.8 percent for a one SD increase in numeracy skills (see pooled model in their Table 2); returns are very similar for literacy skills.[43] Estimated returns to skills are substantially larger—increasing up to 80 percent in some specifications—in IV estimations that use changes in compulsory-schooling laws in the United States as a source of exogenous variation in numeracy skills. This would

[42] We calculated this "ISCED-level equivalent" by regressing ICT skills of PIAAC respondents aged 16–18 years in the 19 sample countries on an indicator that takes the value 1 if the respondent is currently in upper secondary education (ISCED 3A-B, C long); 0 if the respondent is currently in lower secondary education (ISCED 2, 3C short). Regressions control for gender, age, number of books at home at age 15, a migrant indicator, and country fixed effects. The estimate provides an approximation of how much students learn on average transiting from lower secondary to upper secondary education.

[43] The returns estimates are almost unchanged when we re-estimate their model for the 19 countries in our sample.

suggest that more traditional cognitive skills are somewhat more valued on the labor market than ICT skills as measured in PIAAC. However, given that our instruments are likely to isolate a very different complier population than previous estimations (also see analysis below), we shy away from interpreting this comparison as conclusive evidence for the value of ICT skills relative to other types of skill on modern labor markets.

Both IV coefficients are about twice as large as the corresponding OLS results, shown in Columns (1) and (2) of Table 1. These higher returns in the IV specification are likely attributable to measurement error in ICT skills, biasing our results toward zero (see Section 3.1), and that returns are higher for those who give rise to the identifying variation in the IV estimate, namely, the population of compliers. To judge the contribution of measurement error to the returns difference between OLS and IV, we provide two alternative strategies to adjust the estimated coefficient on ICT skills for measurement error. One strategy is to utilize information on the reliability of the ICT-skills test provided by the OECD and the other is to construct two different measures of ICT skills (with uncorrelated measurement errors) from the individual items of the ICT test, allowing to instrument one measure with the other. Both strategies suggest that the measurement-error-corrected effect of ICT skills on wages is about 50-70 percent larger than the baseline OLS estimate (see Online Appendix B for more details).

Since our identification comes from an inverted-U-shaped age pattern in the effect of early broadband availability on ICT skills, we aim to identify the complier population by studying this age pattern for different subgroups of surveyed individuals. Following the returns to schooling literature which suggests that widely-used instruments for schooling differently affect individuals at different education levels (e.g., Card, 2001; Kling, 2001), we explore potential differences in the age pattern of early broadband access for different levels of ICT proficiency.[44] The OECD distinguishes three different ICT-proficiency levels: low (level 1 and below), intermediate (level 2), and high (level 3) (OECD, 2013). In simple linear probability models, we find a pronounced inverted-U-shaped age pattern in the effect of early broadband availability on having an intermediate level of ICT proficiency, while there is no strong age pattern for high ICT proficiency (see Figure A-5).[45] OLS regressions show that the complier population has particularly high returns to ICT skills (see Table A-4, Column (1)).[46]

[44] We did not find pronounced differences in the age pattern for different levels of educational attainment.

[45] Accordingly, the age pattern for low ICT proficiency is U-shaped.

[46] A potential reason for these high returns is occupational selection. We will come back to this issue in Section 6.

There are two further reason for a local average treatment effect (LATE) to arise in the IV regressions. First, our instruments isolate a specific dimension of ICT skills, namely, Internet skills. These were presumably scarcer than overall ICT skills (that also include computer proficiency) in the early phase of broadband diffusion (which is likely most relevant for the estimated learning-by-doing effects), therefore yielding higher rewards on the labor market. Second, differences in the diffusion of fixed lines across countries mainly stem from differences in the provision of fixed lines in rural areas (Falck et al., 2014). We expect that ICT skills are relatively scarce in rural regions, which is another reason for the wage effect of ICT skills to increase in the IV estimations as compared to OLS (see also our discussion of the within-Germany evidence below).

It is worth noting that the complier analysis refutes the potential concern that our results are driven by those individuals who purposefully adopted broadband to accumulate ICT skills because they expected high returns to these skills. The results in Table A-4 suggest that the observed returns to ICT skills are not driven by early adopters, because returns to ICT skills are strongest for persons with intermediate level of ICT skills. In fact, there is a relatively low share of high performers with respect to ICT skills—only 8.5% of the individuals in our sample are at level 3, as compared to 40% at level 2 and 51.5% at level 1 or below. This is clearly at odds with the concern that a substantial fraction of individuals heavily invested in ICT skills because they expected high rewards from them on the labor market. Our results are even very similar when we exclude people with ICT skills at level 3, who are likely the early adopters of broadband due to their high technology affinity and/or the expected reward from investing in ICT skills (results available on request).

### *4.2 Within-Germany Evidence*

Thus far, we have provided evidence on the wage returns to ICT skills from a cross-country IV model. We now zoom in on a single country—Germany—where we exploit historical peculiarities in the voice-telephony network as a source of plausibly exogenous variation in ICT skills. In Columns (5)–(8) of Table 2, we present results from IV regressions using as instrument a dummy variable that equals 1 for municipalities with distances between the municipality centroid and the assigned MDF above the threshold of 4,200 meters. In the full sample, shown in Columns (5) and (6), the first-stage results indicate that persons in municipalities above the 4,200-meter threshold have substantially lower ICT skills than persons living in municipalities below the threshold, which is in accordance with the proposed learning-by-doing channel. In the specification with all controls in Column (6), we find that persons in municipalities with a distant MDF have 0.37 SD lower ICT skills than persons in municipalities with a close MDF.[47] When we use the threshold instrument in a sample of less-agglomerated West German municipalities without an own MDF (Columns (7) and (8)), the magnitude of the threshold estimate increases. Although the threshold instrument has a sizable effect on individual ICT skills, point estimates are somewhat imprecise. A major reason for the relatively low instrument strength is that people are mobile between municipalities, and yet we observe their municipality of residence only at the time of the PIAAC survey in 2011/2012.[48] Although we do not find evidence that the mobility pattern is systematically related to our instrument (see Section IV of Online Appendix C), it is a source of measurement error decreasing instrument strength.[49]

Turning to the second stage of our IV estimation in the upper panel of Table 2, we find that a one SD increase in ICT skills attributable to the technical threshold in broadband availability increases wages by 30.6 percent in the full sample (Column (6)) and by 52.1 percent in the restricted sample (Column (8)). These estimates exceed the returns found in the international analysis, which is consistent with the evidence in Hanushek et al. (2015) that Germany has some of the highest returns to cognitive skills worldwide.[50] Estimated returns in the IV models are about twice as large as in the corresponding OLS specifications, shown in Columns (1)–(4), which again indicates attenuation bias due to measurement error and an interpretation of our IV estimates as local average treatment effects (LATE).[51] However, one reason for the increase in returns in the IV estimation specific to the German identification strategy is that the identifying variation mainly comes from rural areas, where ICT skills are scarcer than on average in the population. One main reason for the relative scarcity of ICT skills in rural areas—which persists despite the higher reward for these skills on the labor market—is that there is generally little mobility to these areas (e.g., because of lacking (cultural) amenities) (see Falck et al., 2014).

[47] Table A-5 provides the complete first-stage results.

[48] Cragg-Donald Wald statistics are no longer valid with clustered standard errors. We therefore report the Kleibergen-Paap F statistic at the bottom of Table 2 to judge instrument strength.

[49] To address a potential weak instrument problem (e.g., Bound et al., 1995), we construct the Anderson and Rubin (AR) 95 percent confidence intervals, which are robust to weak instruments (Anderson and Rubin, 1949). The AR confidence intervals are quite similar to those obtained in the IV estimates, suggesting that our estimates do not suffer from a weak instrument problem that meaningfully biases the IV results (results available upon request).

[50] Large returns in Germany compared to other developed economies are consistent with other analysis that identifies the widening of the income distribution in Germany in recent years; see Card et al. (2013) and Dustmann et al. (2009).

[51] Since the instrument varies only at the municipality level, the OLS results are based on variables aggregated at the municipality level, which provides the correct comparison with IV. One municipality-level SD in ICT skills amounts to 21 PIAAC points, which is half an individual-level SD.

## 5. Assessing the Identification Strategy

In this section, we summarize the results of a series of validity checks, which bolster confidence in our IV strategies. Details on the analyses and on the results can be found in Online Appendix C.

First, we show that our instruments do not predict the ICT skills of first-generation immigrants, who are unlikely to have acquired ICT skills in the PIAAC test country. Nor are the instruments associated with any appreciable changes in numeracy or literacy skills (conditional on ICT skills). Further analysis shows that these residualized numeracy and literacy skills—which we can isolate from ICT skills in our IV approach—have considerable wage returns. This indicates that our identification strategies isolate ICT skills from that part of numeracy and literacy skills that is most relevant for wages. We also show that households in Germany without broadband Internet access do not selectively relocate to regions where broadband is available.

We also provide a careful assessment of the exclusion restriction of our IV approach that exogenous broadband availability affects today's wages only through individuals' ICT skills, and not directly in any other way. There is substantial evidence that broadband affects growth and productivity (e.g., Czernich et al., 2011; Draca et al., 2007). Direct wage effects of broadband would raise concern for identification in the international analysis only if they would be asymmetric across age cohorts, because our IV analysis exploits variation based on differences in the effect of exogenous broadband availability on ICT skills across age cohorts. However, such age pattern in direct broadband effects cannot be ruled out a priori because prior research has shown that certain groups—namely, highly-educated workers and young workers—benefit disproportionally from broadband (e.g., Akerman et al., 2015; Atasoy, 2013; Autor and Dorn, 2009). We thus show that the most prominent channels of direct productivity effects of broadband (increasing firm productivity through the adoption of broadband, introduction of online job search channels improving the quality of job matching) do not exhibit the same non-linear age pattern as our first stage. Moreover, we can even control for direct productivity effects of broadband that are linear in age within countries, industries, and even within detailed country-industry cells.

Further analysis is designed to dispel the concern that our results may be driven by omitted factors correlated with wages and ICT skills, which are heterogeneous across ages. Perhaps most importantly, we account for demand-side considerations by taking into account the differential availability of jobs that provide both higher wages and the opportunity to develop ICT skills. We also provide a comprehensive analysis of whether the cross-country heterogeneity in fixed-line diffusion (which is part of our identification) is truly orthogonal to potential omitted variables that might increase wages of a specific age cohort. First, we explain that the spread of a country's fixed-line network when DSL started to diffuse was mainly determined by the weight that policy-makers put on availability versus affordability and accessibility when the telecom sector was liberalized (OECD, 2006). These differential political weights led to considerable differences in fixed-line diffusion between countries as economically similar as the U.K. and U.S. Second, we extensively control for initial cross-country differences in general technology affinity, spread of ICT-related industries, and economic strength. Estimated returns to ICT skills remain significant and sizeable in all specifications.[52]

## 6. Mechanisms: Job Task Content and Occupational Selection

In this section, we investigate a potential driver of the positive wage returns to ICT skills, namely, that individuals with high ICT skills sort into jobs that are dominated by abstract tasks and pay wage premia. This is in line with the idea that recent technological change amplifies the comparative advantage of those workers engaged in nonroutine abstract tasks. Specifically, Autor et al. (2003) relate changes in the U.S. labor structure since the 1960s to the proliferation of computers in the workplace. The authors ask what kind of tasks computers execute that substitute for or complement tasks performed by workers. Therefore, instead of using conventional labor group distinctions (low-skilled, medium-skilled, and high-skilled; production and nonproduction; or blue-collar and white-collar), they propose a measurement of tasks that provides an intuitive and testable explanation of the relationship between the introduction of new technologies and the demand for heterogeneous labor. The basic idea is that computers substitute for routine tasks (those that can be accomplished by following explicit rules) and are complementary to nonroutine abstract tasks (such as problem solving, adaptability, and creativity). The underlying reasoning is that routine tasks embody explicit knowledge that can be relatively easily programmed, which is not the case for abstract tasks. Moreover, an increase in the supply of codifiable tasks increases the marginal productivity of employees who engage extensively in abstract tasks and who use routine work output as their work input.[53]

The increasing importance of abstract tasks may be a driver of our result that ICT skills are considerably rewarded on modern labor markets. If high ICT skills are required to obtain jobs that are

[52] In Online Appendix D, we assess the robustness of our estimates to additional controls and changes in the sample.

[53] Recent evidence suggests that such skill complementarity of personal computers is also present in Europe (Akerman et al., 2015).

pervasive at abstract tasks because these tasks are complementary to computers, any wage premium attached to abstract jobs would imply positive returns to ICT skills. To analyze whether occupational selection is an avenue through which ICT skills lead to higher wages, we estimate our baseline IV models replacing hourly wages with the occupational task content. For this analysis, we gained access from the OECD to the two-digit ISCO-08 (International Standard Classification of Occupations) codes for all employed PIAAC respondents. We link these occupational codes to the measures of abstract, routine, and manual tasks from Goos et al. (2014).[54] Additionally, we also classify occupations by computer use by PIAAC respondents, that is, the frequency of using software, programming language, and spreadsheet tools at work.

Table 3 shows the results for the international sample; Table 4 provides the findings for the German analysis. Throughout specifications and samples, higher ICT skills increase the abstract task content of jobs and the intensity of computer use at work. At the same time, an increase in ICT skills decreases the routine and manual intensity of jobs.[55] The magnitudes of the effects are considerable: in the international analysis, a one SD increase in ICT skills leads to a 0.80 SD increase in the abstract intensity of a job (e.g., from a business and administration associate to a business and administration professional or from an assembler to a sales worker). Likewise, the routine task content of jobs decreases by 0.41 SD for a one SD increase in ICT skills (e.g., from a plant and machine operator to a science and engineering associate or from a laborer in mining, construction, and manufacturing to a health professional).

To further explore the interpretation of our IV results as local average treatment effects (see Section 4.1), we show that the effect of ICT skills on the sorting into jobs with a high abstract and low routine/manual task content is mainly driven by individuals with intermediate ICT proficiency (Table A-4, Columns (2)-(4)). While individuals with high ICT proficiency (level 3) are most likely to work in abstract-intense jobs, further increases in their ICT skills do not contribute as much to an increase in the abstract intensity of jobs as is the case for workers with intermediate ICT proficiency. This suggests that crossing a certain ICT-skill threshold allows individuals to enter abstract-intense jobs.

A potential concern with this analysis is that the results may be driven by age-biased job reallocations, as highlighted by Autor and Dorn (2009). Specifically, young workers (with relatively high

[54] Workers with the highest abstract job content in our sample are managers and teaching professionals. Occupations with the lowest abstract content are elementary occupations (e.g., cleaners and helpers).

[55] These estimates are not statistically significant in the full German sample.

average ICT skills) may not yet have acquired much occupation-specific human capital and may develop new skills relatively easily, so they are more likely to manage transitions from routine to abstract jobs than are older workers (with relatively low average ICT skills). However, we do not observe a clear age pattern in any of the job tasks (see Figure A-6). If anything, individuals working in jobs that make intense use of abstract tasks or computers are relatively old and workers in jobs that are pervasive at routine or manual tasks are relatively young. This also adds to our discussion of potential age-specific omitted variables (see Section III of Online Appendix C).

Our results show that the proliferation of computers is an important mechanism behind the positive returns to ICT skills on modern labor markets. Jobs that heavily involve abstract tasks pay substantial wage premia, as shown at the bottom of Tables 3 and 4, and having high ICT skills appears to be a prerequisite for obtaining these well-paid jobs. Employing back-of-the-envelope calculations, we can provide an idea of how much of the returns to ICT skills can be explained by occupational selection. In regressions of log hourly wages on abstract, routine, and manual task scores, and conditioning on age cohort dummies, female indicator, and country fixed effects, we find that a one SD increase in abstract task content is associated with a 21.3 percent increase in hourly wages, whereas a one SD increase in routine (manual) task content is associated with a 5.2 (2.1) percent increase (decrease) in wages. Multiplying the effect of ICT skills on the occupational task content by the task-wage associations gives: 0.803*21.3 – 0.406*5.2 – 0.343*(-2.1) = 15.7. Based on this simple calculation, occupational selection explains about two-thirds (15.7/23.6=0.665) of the wage increase due to higher ICT skills in the international sample. The conclusion that higher ICT skills mainly pay off because of occupational selection is corroborated when we estimate our baseline wage regression augmented by the occupational task content (results not shown). We find that that estimated returns to ICT skills decrease by about one-half and become statistically insignificant when an occupation's abstract or manual task intensity is included as control. Once all three task measures are jointly included, returns to ICT skills are close zero. The same is true when we control for occupational fixed effects instead of task intensities.

## 7. Summary and Policy Conclusions

How important is mastering ICT for today's employees? As of yet, there is no convincing empirical evidence on how the labor market rewards ICT skills. The main reasons for this lack of evidence are the unavailability of data that measure ICT skills consistently within or across countries, and the difficulty of drawing credible inferences when it is unknown whether an individual's level of ICT skills is simply a reflection of general ability. Using novel, internationally comparable data on individuals' skills in ICT and other domains across 19 countries, we provide the first systematic assessment of the wage returns to ICT skills. Our identification strategy is based on the idea that ICT skills are developed through learning-by-doing, which is facilitated by (early) Internet access. We implement two IV strategies that exploit technology-induced variation in Internet availability across countries and across small geographical areas within a single country, Germany.

We find statistically and economically significant returns to ICT skills: a one SD increase in ICT skills leads to an almost 24 percent increase in wages in the international sample and to an increase of 31 percent in the German sample. Placebo tests showing that the variables that exogenously determine Internet access cannot explain any meaningful variation in numeracy or literacy skills suggest that our IV models isolate the wage effect of ICT skills from that of general ability. One mechanism driving positive returns to ICT skills is selection into occupations with high abstract task content, allowing workers with high ICT skills to benefit from the wage premia these jobs pay.

Our findings are relevant for the ongoing debate on social inequality in access to the Internet, also known as the "digital divide." [56] Our fundamental insight—that ICT skills can be promoted by providing access to ICT infrastructure—suggests that the efforts by policy-makers worldwide to expand broadband Internet access may prevent a drifting apart in employment opportunities when advances in technology change job demands (e.g., Acemoglu and Restrepo, 2018, 2020; Autor et al., 1998). Therefore, it is crucial to ensure Internet access also for those who are socially disadvantaged or live in remote areas (Zuo and Kolliner, 2019).

This policy conclusion is in contrast to Vigdor et al. (2014), who argue that the digital divide is actually beneficial for disadvantaged groups because—based on available evidence—providing better access to technology would broaden even further the math and reading achievement gap between rich and poor. Their conclusion, however, ignores the fact that the skills needed to master technology are substantially rewarded on today's labor market.

Additionally, it is vital for governments to promote adequate life-long-learning opportunities on a labor market that is rapidly changing (Vona and Consoli, 2015). In particular, structural and technological change will likely raise the demand for expertise in ICT-related tasks in the future. On the one hand, continuous training opportunities especially for older employees must be provided, as these workers have lower ICT skills than their younger counterparts (Figure A-1). Multivariate evidence from

[56] For instance, linking data from the 2013 American Community Survey with the most recent version of the National Broadband Map, President Obama's Council of Economic Advisors shows that black and Hispanic households in the United States are 16 and 11 percentage points, respectively, less likely to have an Internet connection than are white households (CEA, 2015).

the PIAAC data shows a positive association between training participation and (ICT) skills for all age groups (Table A-6). However, workers aged 55–65 (i.e., the oldest age group in PIAAC) have a lower training participation rate than their prime-age peers (see bottom of Table A-6). Thus, governments may try to incentivize training participation epically of older workers or, more generally, of groups of workers with low training participation rates.

On the other hand, future generations must already be properly trained before entering the labor market. In particular, the ability to adapt to change is gaining in importance. The flexibility that is needed to master the increasing digitization and automation (for a discussion of recent developments, see Agrawal et al., 2017 and Zysman and Kenney, 2018) not only entails digital skills, but also social skills (Deming, 2017), non-cognitive skills (e.g., conscientiousness: Almlund et al., 2011; grit: Alan et al., 2019), basic competencies (Hanushek and Woessmann, 2008), as well as transversal skills (e.g., ability to learn new things, adaptability, collaborative problem-solving, creativity, critical thinking, cultural awareness, and metacognition; see Stifterverband, 2018 and Whittemore, 2018).[57]

However, the importance of expertise in ICT goes beyond employment opportunities and wage returns. Technological change will likely raise the demand for ICT skills in various areas in everyday life. The provision of digital public services and Internet voting are two prominent examples. For instance, Estonia is known to be a forerunner in these areas; at the same time, however, Estonia is at the bottom of the international league table in ICT skills, just above the worst performing country, Poland (Figure 1). This poor performance in terms of average ICT skills in Estonia primarily comes from a particularly strong decay in ICT skills for older age cohorts (Figure A-7), who had less opportunity to acquire those skills early in life at a time when Estonia was still part of the Soviet Union.[58] Being unable to master ICT skills in a heavily digitized environment (as is the case in Estonia today) may eventually become a question of social participation.

[57] These are also frequently referred to as "21st century skills" in the policy debate.

[58] The differential age decay in ICT skills between Estonia and the full-sample average as suggested by Figure A-7 is likely even an underestimation of the true age-skills gradient. Figure A-8 shows the probability to participate in ICT skills assessment for Estonia vs. internationally. While the participation probability is very similar in Estonia compared to the country average for the 20–34 year olds, the gap widens by age, being largest for the oldest cohort of 55–65 year olds.

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## References


Acemoglu, Daron (1998): "Why Do New Technologies Complement Skills? Directed Technical Change and Wage Inequality." *Quarterly Journal of Economics*, 113(4): 1055–1089.

Acemoglu, Daron and David H. Autor (2011): "Skills, Tasks and Technologies: Implications for Employment and Earnings." *Handbook of Labor Economics* (Orley Ashenfelter and David Card, Eds.), Vol. 4, 1043–1171. Amsterdam: Elsevier.

Acemoglu, Daron and Pascual Restrepo (2018): "The Race between Man and Machine: Implications of Technology for Growth, Factor Shares, and Employment." *American Economic Review*, 108(6): 1488–1542.

Acemoglu, Daron and Pascual Restrepo (2020): "Robots and Jobs: Evidence from US Labor Markets." *Journal of Political Economy*, 128(6): 2188-2244.

Aghion, Philippe and Peter Howitt (1992): "A Model of Growth through Creative Destruction." *Econometrica*, 60(2): 323–351.

Aghion, Philippe, and Peter Howitt (1998): Endogenous Growth Theory. Cambridge, MA: MIT Press

Agrawal, Ajay, Joshua Gans and Avi Goldfarb (2017): The Economics of Artificial Intelligence: An Agenda. University of Chicago Press.

Akerman, Anders, Ingvil Gaarder, and Magne Mogstad (2015): "The Skill Complementarity of Broadband Internet." *Quarterly Journal of Economics*, 130(4): 1781–1824.

Alan, Sule, Teodora Boneva, and Seda Ertac (2019): "Ever Failed, Try Again, Succeed Better: Results from a Randomized Educational Intervention on Grit." *Quarterly Journal of Economics*, 134(3): 1121–1162.

Almlund, Mathilde, Angela Lee Duckworth, James J. Heckman, and Tim D. Kautz (2011): "Personality Psychology and Economics." *Handbook of the Economics of Education* (Eric A. Hanushek, Steven Machin, and Ludger Woessmann, Eds.), Vol. 4, 1–181. Amsterdam: North-Holland.

Anderson, T. W. and Herman Rubin (1949): "Estimation of the Parameters of a Single Equation in a Complete System of Stochastic Equations." *Annals of Mathematical Statistics*, 20(1): 46–63.

Angrist, Joshua D. and Alan B. Krueger (1991): "Does Compulsory Attendance Affect Schooling and Earnings?" *Quarterly Journal of Economics*, 106(4): 979–1014.

Atasoy, Hilal (2013): "The Effects of Broadband Internet Expansion on Labor Market Outcomes." *ILR Review*, 66(2): 315–345.

Autor, David H. (2015): "Why Are There Still So Many Jobs? The History and Future of Workplace Automation." *Journal of Economic Perspectives*, 29(3): 3–30.

Autor, David H. and David Dorn (2009): "The Skill Content of Jobs and the Evolution of the Wage Structure—This Job is 'Getting Old': Measuring Changes in Job Opportunities Using Occupational Age Structure." *American Economic Review: Papers & Proceedings*, 99(2): 45–51.

Autor, David H. and David Dorn (2013): "The Growth of Low-Skill Service Jobs and the Polarization of the US Labor Market." *American Economic Review*, 103(5): 1553–1597.

Autor, David H., Lawrence F. Katz, and Melissa S. Kearney (2006): "The Polarization of the U.S. Labor Market." *American Economic Review Papers and Proceedings*, 96(2): 189–194.

Autor, David H., Lawrence F. Katz, and Melissa S. Kearney (2008): "Trends in US Wage Inequality: Revising the Revisionists." *Review of Economics and Statistics*, 90(2): 300–323.

Autor, David H., Lawrence F. Katz and Alan Krueger (1998): "Computing Inequality: Have Computers changed the Labor Market?" *Quarterly Journal of Economics*, 113(4): 1169–1214.

Autor, David H., Frank Levy, and Richard J. Murnane (2003): "The Skill Content of Recent Technological Change: An Empirical Exploration." *Quarterly Journal of Economics*, 118(4): 1279–1333.

Barro, Robert J. and Jong Wha Lee (2013): "A New Data Set of Educational Attainment in the World, 1950–2010." *Journal of Development Economics*, 104(C): 184–198.

Bauernschuster, Stefan, Oliver Falck, and Ludger Woessmann (2014): "Surfing Alone? The Internet and Social Capital: Quasi-Experimental Evidence from an Unforeseeable Technological Mistake." *Journal of Public Economics*, 117: 73–89.

Benhabib, Jess and Mark M. Spiegel (2005): "Human Capital and Technology Diffusion." *Handbook of Economic Growth* (Philippe Aghion and Steven N. Durlauf, Eds.), 935–966. Amsterdam: North Holland.

Bertschek, Irene, Daniel Cerquera, and Gordon Jochem Klein (2013): "More Bits—More Bucks? Measuring the Impact of Broadband Internet on Firm Performance." *Information Economics and Policy*, 25(3): 190–203.

Bhuller, Manudeep, Tarjei Havnes, Edwin Leuven, and Magne Mogstad (2013): "Broadband Internet: An Information Superhighway to Sex Crime?" *Review of Economic Studies,* 80(4): 1237–1266.

Black, Sandra E. and Alexandra Spitz-Oener (2010): "Explaining Women's Success: Technological Change and the Skill Content of Women's Work." *Review of Economics and Statistics*, 92(1): 187–194.

Borghans, Lex and Bas ter Weel (2004): "Are Computer Skills the New Basic Skills? The Returns to Computer, Writing and Math Skills in Britain." *Labour Economics*, 11(1): 85–98.

Bound, John, David A. Jaeger, and Regina M. Baker (1995): "Problems with Instrumental Variables Estimation When the Correlation Between the Instruments and the Endogenous Explanatory Variable is Weak." *Journal of the American Statistical Association*, 90(430): 443–450.

Bresnahan, Timothy F., Erik Brynjolfsson, and Lorin M. Hitt (2002): "Information Technology, Workplace Organization, and the Demand for Skilled Labor: Firm-Level Evidence." *Quarterly Journal of Economics*, 117(1): 339–376.

Bulman, George and Robert W. Fairlie (2016): "Technology and Education: Computers, Software, and the Internet." NBER Working Paper No. 22237.

Cameron, A. Colin, Jonah B. Gelbach, and Douglas L. Miller (2008): "Bootstrap-Based Improvements for Inference with Clustered Errors." *Review of Economics and Statistics*, 90(3): 414–427.

Card, David (1999): "The Causal Effect of Education on Earnings." *Handbook of Labor Economics* (Orley Ashenfelter and David Card, Eds.), Vol. 3, 1801–1863. Amsterdam: North-Holland.

Card, David (2001): "Estimating the Return to Schooling: Progress on Some Persistent Econometric Problems." *Econometrica*, 69(5): 1127–1160.

Card, David, Joerg Heining and Patrick Kline (2013): "Workplace Heterogeneity and the Rise of West German Wage Inequality." *Quarterly Journal of Economics*, 128(3): 967–1015.

CEA (2015): "Mapping the Digital Divide." Council of Economic Advisors Policy Brief, August 2015.

Cortes, Guido Matias (2016): "Where Have the Middle-Wage Workers Gone? A Study of Polarization Using Panel Data." *Journal of Labor Economics*, 34(1): 63–105.

Czaja, Sara J., Neil Charness, Arthur D. Fisk, Christopher Hertzog, Sankaran N. Nair, Wendy A. Rogers, and Joseph Sharit (2006): "Factors Predicting the Use of Technology: Findings from the Center for

Research and Education on Aging and Technology Enhancement (CREATE)." *Psychology and Aging*, 21(2): 333–352.

Czernich, Nina, Oliver Falck, Tobias Kretschmer, and Ludger Woessmann (2011): "Broadband Infrastructure and Economic Growth." *Economic Journal*, 121: 505–532.

Deming, David (2017): "The Growing Importance of Social Skills in the Labor Market." *Quarterly Journal of Economics*, 132(4): 1593–1640.

DiNardo, John E. and Joern-Steffen Pischke (1997): "The Returns to Computer Use Revisited: Have Pencils Changed the Wage Structure Too?" *Quarterly Journal of Economics*, 112(1): 291–303.

Dolton, Peter and Gerry Makepeace (2004): "Computer Use and Earnings in Britain." *Economic Journal*, 114(494): C117-129.

Draca, Mirko, Raffaella Sadun, and John Van Reenen (2007): "Productivity and ICTs: A Review of the Evidence." *Oxford Handbook of Information and Communication Technologies* (Robin Mansell, Chrisanthi Avgerou, Danny Quah, and Roger Silverstone, Eds.), 100–147. Oxford: Oxford University Press.

Dustmann, Christian, Johannes Ludsteck, and Uta Schoenberg (2009): "Revisiting the German Wage Structure." *Quarterly Journal of Economics*, 124(2): 843–881.

Faber, Benjamin, Rosa Sanchis-Guarner, and Felix Weinhardt (2015): "ICT and Education: Evidence from Student Home Addresses." NBER Working Paper No. 21306.

Falck, Oliver, Robert Gold, and Stephan Heblich (2014): "E-lections: Voting Behavior and the Internet." *American Economic Review*, 104(7): 2238–2265.

Fairlie, Robert W. and Peter Riley Bahr (2017): "The Labor Market Returns to Computer Skills: Evidence from a Field Experiment and California UI Earnings Records." SIEPR Discussion Paper No. 17-015.

Federal Statistical Office (2012): *Unternehmen und Arbeitsstaetten: Nutzung von Informations- und Kommunikationstechnologien in Unternehmen*. Wiesbaden, Germany: Federal Statistical Office.

Firpo, Sergio P., Nicole M. Fortin, and Thomas Lemieux (2011): "Occupational Tasks and Changes in the Wage Structure." IZA Discussion Paper No. 5542.

Gaggl, Paul and Greg C. Wright (2017): "A Short-Run View of What Computers Do: Evidence from a UK Tax Incentive." *American Economic Journal: Applied Economics*, 9(3): 262–294.

Geroski, Paul (2000): "Models of Technology Diffusion." *Research Policy*, 29(4–5): 603–625.

Goldin, Claudia and Lawrence F. Katz (2008): *The Race Between Education and Technology*. Harvard: Harvard University Press.

Goos, Maarten and Alan Manning (2007): "Lousy and Lovely Jobs: The Rising Polarization of Work in Britain." *Review of Economics and Statistics*, 89(1): 118–133.

Goos, Maarten, Alan Manning, and Anna Salomons (2014): "Explaining Job Polarization: Routine-Biased Technological Change and Offshoring." *American Economic Review*, 104(8): 2509–2526.

Griliches, Zvi (1957): "Hybrid Corn: An Exploration in the Economics of Technological Change." *Econometrica*, 25(4): 501–522.

Hanushek, Eric A., Guido Schwerdt, Simon Wiederhold, and Ludger Woessmann (2015): "Returns to Skills Around the World: Evidence from PIAAC." *European Economic Review*, 73(C): 103–130.

Hanushek, Eric A. and Ludger Woessmann (2008): "The Role of Cognitive Skills in Economic Development." *Journal of Economic Literature*, 46(3): 607–668.

Heckman, James J., Lance J. Lochner, and Petra E. Todd (2006): "Earnings Functions, Rates of Return and Treatment Effects: The Mincer Equation and Beyond." *Handbook of the Economics of Education* (Eric A. Hanushek and Finis Welch, Eds.), Vol. 1, 307–458. Amsterdam: North Holland.

Kling, Jeffrey R. (2001): "Interpreting Instrumental Variables Estimates of the Returns to Schooling." *Journal of Business & Economic Statistics*, 19(3): 358–364.

Kling, Jeffrey R., Jeffrey B. Liebman, and Lawrence F. Katz (2007): "Experimental Analysis of Neighborhood Effects." *Econometrica*, 75(1): 83–119.

Krueger, Alan B. (1993): "How Computers Have Changed the Wage Structure: Evidence from Microdata, 1984–1989." *Quarterly Journal of Economics*, 108(1): 33–60.

Malamud, Ofer and Cristian Pop-Eleches (2011): "Home Computer Use and the Development of Human Capital." *Quarterly Journal of Economics*, 126(2): 987–1027.

Mincer, Jacob (1970): "The Distribution of Labor Incomes: A Survey with Special Reference to the Human Capital Approach." *Journal of Economic Literature*, 8(1): 1–26.

Mincer, Jacob (1974): *Schooling, Experience, and Earnings*. New York: NBER.

Moulton, Brent R. (1986): "Random Group Effects and the Precision of Regression Estimates." *Journal of Econometrics*, 32(3): 385–397.

Moulton, Brent R. (1990): "An Illustration of a Pitfall in Estimating the Effects of Aggregate Variables on Micro Units." *Review of Economics and Statistics*, 72(2): 334–338.

Nelson, Richard R. and Edmund Phelps (1966): "Investment in Humans, Technology Diffusion and Economic Growth." *American Economic Review*, 56(2): 69–75.

OECD (2006): *Rethinking Universal Service for a Next Generation Network Environment*. Paris: Organisation for Economic Co-operation and Development.

OECD (2013): *OECD Skills Outlook 2013. First Results from the Survey of Adult Skills*. Paris: Organisation for Economic Co-operation and Development.

OECD (2015): *Adults, Computers and Problem Solving: What's the Problem?* Paris: Organisation for Economic Co-operation and Development.

Perry, Anja, Simon Wiederhold, and Daniela Ackermann-Piek (2014): "How Can Skill Mismatch Be Measured? New Approaches with PIAAC." *methods data analyses—Journal for Quantitative Methods and Survey Methodology*, 8(2): 137–174.

Pew Internet and American Life Project (2002): "The Broadband Difference—How Online Americans' Behavior Changes with High-Speed Internet Connections at Home." Available at: http://www.pewinternet.org/files/old-media//Files/Reports/2002/PIP_Broadband_Report.pdf.pdf; accessed: January 12, 2018.

Rammstedt, Beatrice (Ed.). (2013): *Grundlegende Kompetenzen Erwachsener im internationalen Vergleich: Ergebnisse von PIAAC 2012*. Muenster: Waxmann.

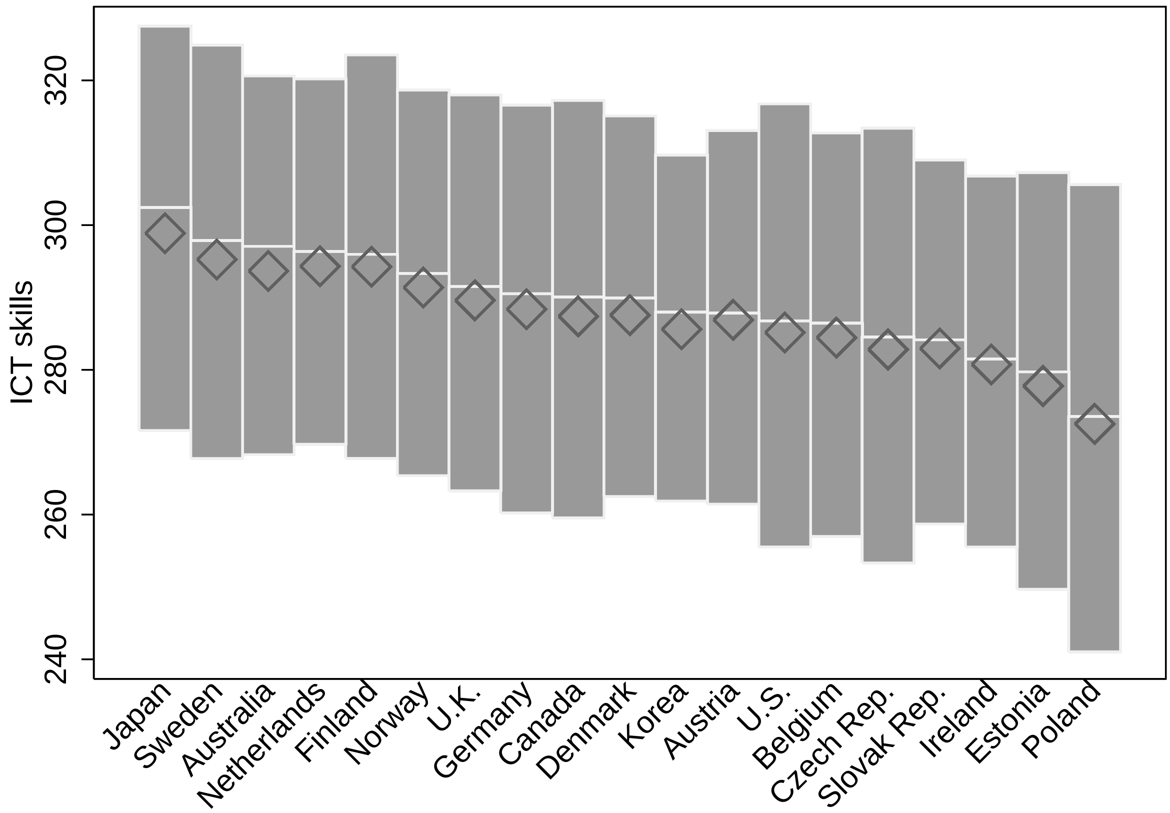
Roeller, Lars-Hendrik and Leonard Waverman (2001): "Telecommunications Infrastructure and Economic Development: A Simultaneous Approach." *American Economic Review*, 91(4): 909–923.

Romer, Paul M. (1990): "Endogenous Technological Change." *Journal of Political Economy*, 99(5), pt. II: S71–S102.

Spitz-Oener, Alexandra (2006): "Technical Change, Job Tasks and Rising Educational Demands: Looking Outside the Wage Structure." *Journal of Labor Economics*, 24(2): 235–270.

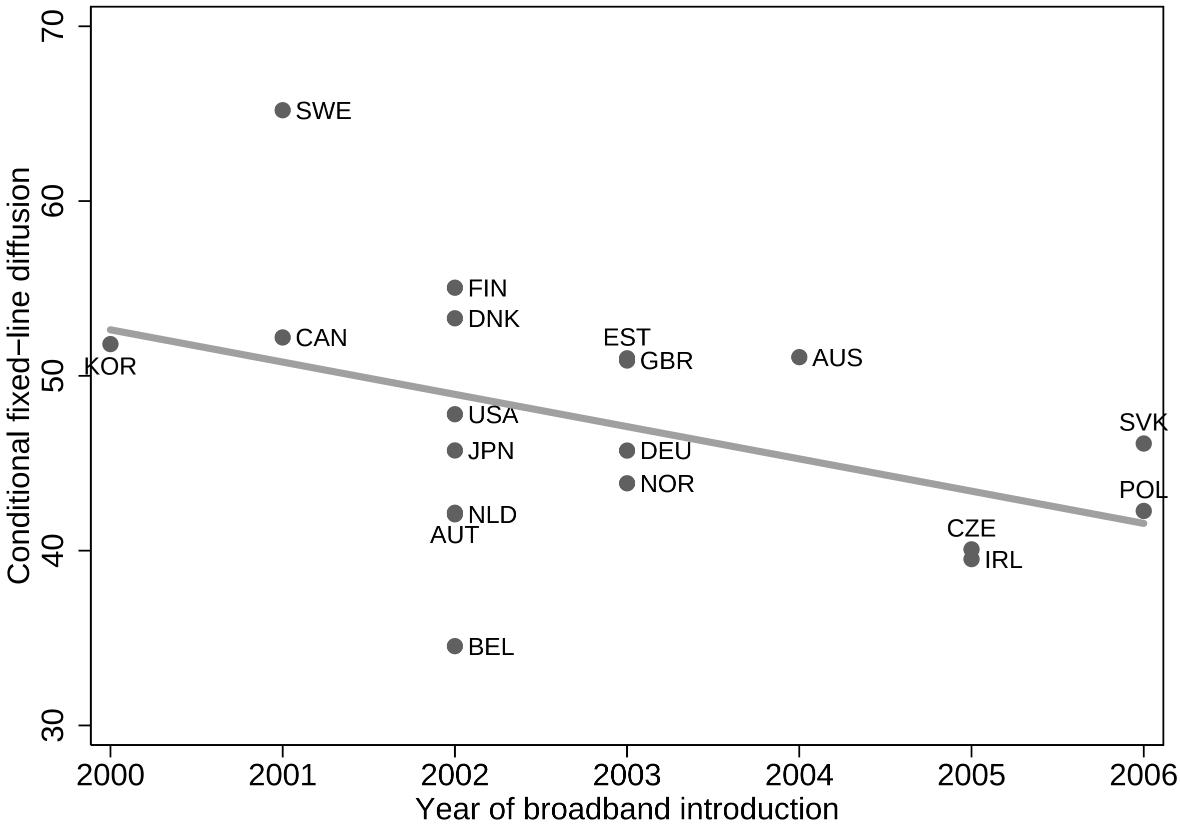
Spitz-Oener, Alexandra (2008): "The Returns to Pencil Use Revisited." *Industrial and Labor Relations Review*, 61(4): 502–517.
Stifterverband (2018), Future Skills: Welche Kompetenzen in Deutschland fehlen. Future Skills – Diskussionspapier 1.
Stock, James H. and Motohiro Yogo (2005): "Testing for Weak Instruments in Linear IV Regression." *Identification and Inference for Econometric Models: Essays in Honor of Thomas Rothenberg* (Donald W. K. Andrews and James H. Stock, Eds.), 80–108. New York: Cambridge University Press.
Vigdor, Jacob L., Helen F. Ladd, and Erika Martinez (2014): "Scaling the Digital Divide: Home Computer Technology and Student Achievement." *Economic Inquiry*, 52(3): 1103–1119.
Vona, Francesco and Davide Consoli (2015): "Innovation and Skill Dynamics: A Life-Cycle Approach." *Industrial and Corporate Change*, 24(6): 1393–1415.
Welch, Finis (1970): "Education in production." *Journal of Political Economy*, 78(1): 35–59.
Whittemore, Simon (2018). "Transversal Competencies Essential for Future Proofing the Workforce." White Paper. Macerata: Skilla.
Zuo, George and Daniel Kolliner (2019): "Wired and Hired: Employment Effects of Subsidized Broadband Internet for Low-Income Americans." Working Paper.
Zysman, John and Martin Kenney (2018): "The Next Phase in the Digital Revolution: Abundant Computing, Platforms, Growth, and Employment." *Communications of the Association of Computing Machinery*, 61(2): 54–63.

Figure 1: ICT Skills Around the World



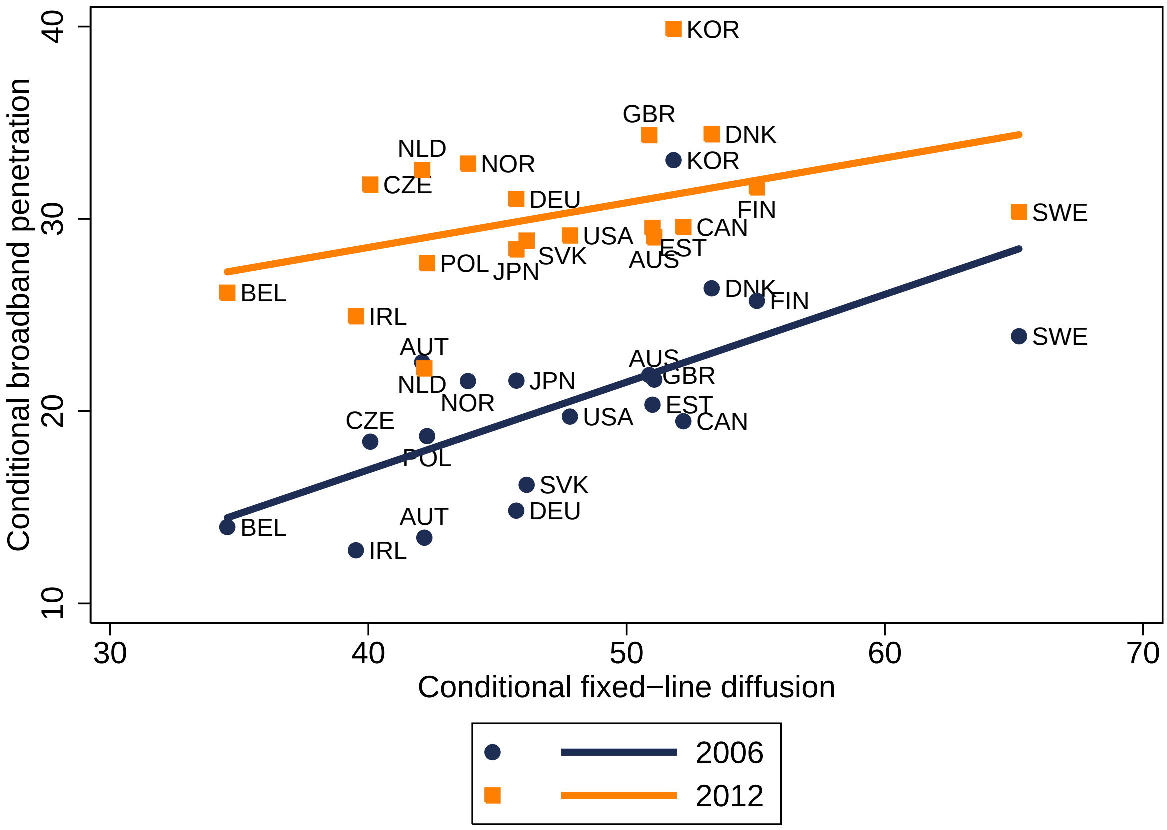

*Notes:* Graph shows ICT skills by country. White bars indicate median ICT skills, diamonds indicate mean ICT skills, and boxes indicate the 25th–75th percentile ICT skill range. Countries are ordered by median ICT skills. Sample: employees aged 20–65 years, no first-generation immigrants. *Data source:* PIAAC.

Figure 2: Effect of Fixed-Line Diffusion on Broadband Introduction



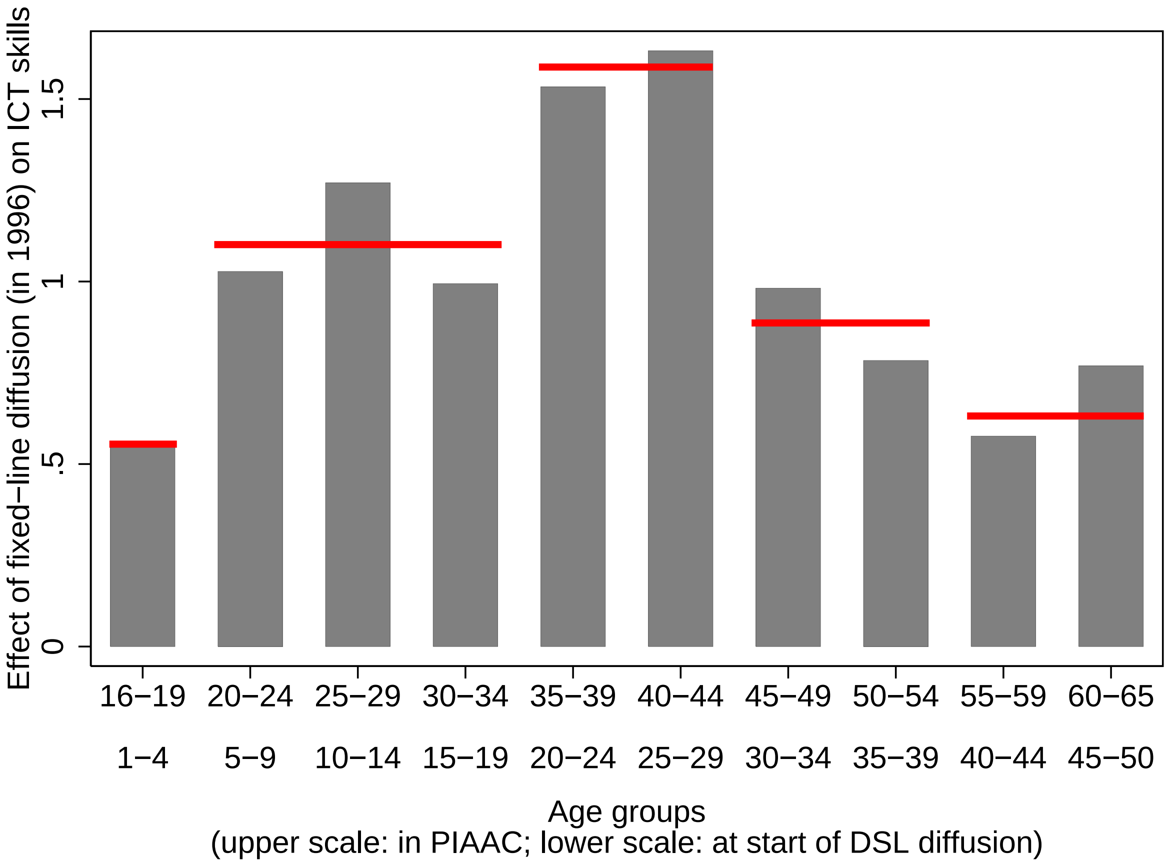

*Notes:* Graph shows the relationship between fixed-line diffusion in 1996 (conditional on control variables) and first emergence of broadband in a country. Fixed-line diffusion is the number of telephone access lines per 100 inhabitants in 1996. Year of broadband introduction in this graph is the year when broadband penetration (i.e., the number of broadband subscriptions per inhabitant) first exceeded 5 percent. Control variables are GDP per capita in 1996 (in logs), years of schooling in 1995, population size in 1995, and cable TV diffusion (measured as cable television subscriptions per inhabitant) in 1996. *Data sources:* Barro and Lee (2013), ITU, OECD.

Figure 3: Effect of Fixed-Line Diffusion on Broadband Penetration: 2006 vs. 2012



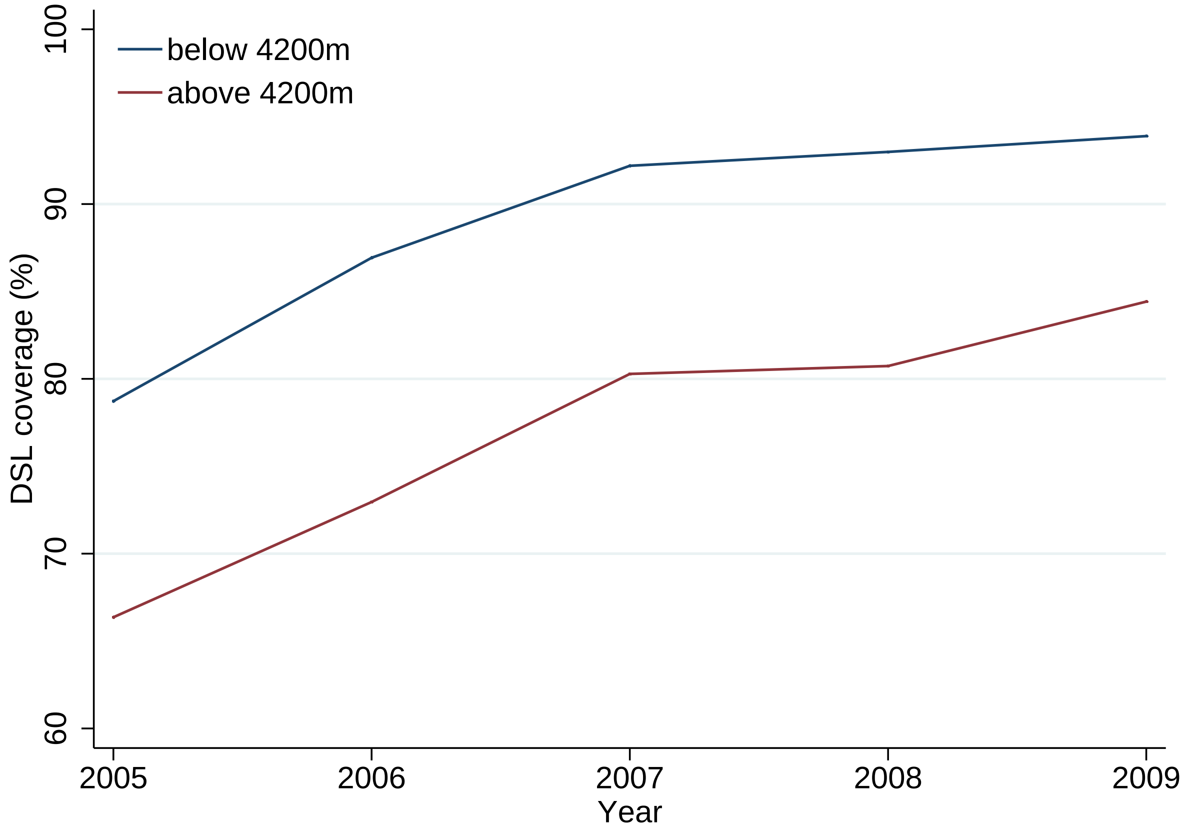

*Notes:* Graph shows country-level added-variable plots from regressing broadband penetration in 2006 (dark navy) or 2012 (orange) on fixed-line diffusion in 1996 and control variables. Broadband penetration is the number of broadband subscriptions per inhabitant. Fixed-line diffusion is the number of telephone access lines per 100 inhabitants in 1996. Control variables are GDP per capita in 1996 (in logs), years of schooling in 1995, population size in 1995, and cable TV diffusion (measured as cable television subscriptions per inhabitant) in 1996. *Data sources:* Barro and Lee (2013), ITU, OECD.

Figure 4: Preexisting Fixed-Line Diffusion and ICT Skills by Age Group




*Notes:* Coefficient estimates on fixed-line voice-telephony diffusion (in 1996) for indicated age groups in a regression of ICT skills (standardized to SD 1 across countries) on fixed-line diffusion. Regression weighted by sampling weights (giving same weight to each country). Sample: employees, no first-generation immigrants. Solid lines show average effect of fixed-line diffusion on ICT skills by age groups (separately for ages 16–19, 20—34, 35–44, 45-–54, and 55–65). *Data sources:* ITU, PIAAC.

Figure 5: DSL Coverage in Above-Threshold and Below-Threshold Municipalities




*Notes:* The figure shows the share of households with access to DSL in the period 2005–2009. The blue (red) line indicates municipalities that are less (more) than 4,200 meters away from their assigned MDF. *Data sources:* German Broadband Atlas, German Federal Statistical Office.

Table 1: Returns to ICT Skills: International Evidence

| Dependent variable: log gross hourly wage | OLS | | 2SLS (second stage) | |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| ICT skills | 0.115*** | 0.122*** | 0.232*** | 0.236*** |
| | (0.003) | (0.003) | (0.080) | (0.078) |
| Age 20–34 | –0.339*** | –0.359*** | –0.438*** | –0.457*** |
| | (0.009) | (0.008) | (0.070) | (0.069) |
| Age 35–44 | –0.103*** | –0.118*** | –0.177*** | –0.191*** |
| | (0.009) | (0.008) | (0.055) | (0.053) |
| Age 45–54 | –0.034*** | –0.051*** | –0.070*** | –0.086*** |
| | (0.009) | (0.008) | (0.027) | (0.026) |
| Female | –0.151*** | –0.161*** | –0.137*** | –0.148*** |
| | (0.005) | (0.005) | (0.011) | (0.010) |
| Fixed-line diffusion | 1.907*** | | 1.781*** | |
| | (0.021) | | (0.090) | |
| Country fixed effects | | X | | X |
| First stage (Dependent variable: ICT skills) | | | | |
| Fixed-line diffusion | | | 0.554*** | |
| | | | (0.141) | |
| Fixed-line diffusion × age 20–34 | | | 0.505*** | 0.384** |
| | | | (0.155) | (0.155) |
| Fixed-line diffusion × age 35–44 | | | 0.920*** | 0.839*** |
| | | | (0.169) | (0.168) |
| Fixed-line diffusion × age 45–54 | | | 0.288* | 0.253 |
| | | | (0.171) | (0.170) |
| Cragg-Donald Wald F statistic | | | 32.5 | 28.5 |
| Stock & Yogo critical value | | | 9.1 | 9.1 |
| Individuals | 53,879 | 53,879 | 53,879 | 53,879 |

*Notes:* Regressions weighted by sampling weights (giving same weight to each country). Least squares estimations in Columns (1) and (2); two-stage least squares estimations in Columns (3) and (4). Sample: employees aged 20–65 years, no first-generation immigrants. Dependent variable in second stage, *log gross hourly wage*, is measured in PPP-USD. ICT skills are standardized to SD 1 across countries. *Fixed-line diffusion:* voice-telephony penetration rate (telephone access lines per inhabitant) in 1996. Omitted age category is 55–65 years. Robust standard errors in parentheses. Significance levels: * $p<0.10$, ** $p<0.05$, *** $p<0.01$. *Data sources:* ITU, PIAAC.

Table 2: Returns to ICT Skills: Within-Germany Evidence

| Dependent variable: log gross hourly wage | OLS (municipality level) | | | | 2SLS (second stage) | | | |
|---|---|---|---|---|---|---|---|---|
| | Full sample | | No own MDF sample | | Full sample | | No own MDF sample | |
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
| ICT skills | 0.136*** | 0.148*** | 0.209*** | 0.271*** | 0.272 | 0.306** | 0.405** | 0.521** |
| | (0.025) | (0.025) | (0.079) | (0.087) | (0.167) | (0.151) | (0.204) | (0.213) |
| Unemployment rate in 1999 | 0.272 | 0.796 | 1.412 | 0.989 | 0.557 | 1.229* | 3.153 | 0.539 |
| | (0.585) | (0.556) | (2.691) | (2.169) | (0.726) | (0.677) | (3.027) | (4.436) |
| Population share 65+ in 1999 | –0.570 | –0.533 | –0.285 | –1.041 | –0.436 | –0.215 | –1.430 | 0.483 |
| | (0.587) | (0.514) | (1.567) | (1.674) | (0.641) | (0.448) | (2.298) | (2.477) |
| Experience | | 0.044*** | | 0.092 | | 0.053*** | | 0.046*** |
| | | (0.011) | | (0.072) | | (0.004) | | (0.013) |
| Experience$^2$ (/100) | | –0.085*** | | –0.214 | | –0.074*** | | –0.031 |
| | | (0.024) | | (0.165) | | (0.012) | | (0.033) |
| Female | | –0.190** | | 0.039 | | –0.138*** | | –0.057 |
| | | (0.078) | | (0.655) | | (0.035) | | (0.118) |
| First stage (Dependent variable: ICT skills) | | | | | | | | |
| Threshold | | | | | –0.404*** | –0.369*** | –0.592*** | –0.517*** |
| | | | | | (0.102) | (0.114) | (0.126) | (0.153) |
| Kleibergen-Paap F statistic | | | | | 15.8 | 10.5 | 22.1 | 11.5 |
| Individuals | - | - | - | - | 1,849 | 1,849 | 160 | 160 |
| Municipalities | 204 | 204 | 18 | 18 | 204 | 204 | 18 | 18 |

*Notes:* Regressions weighted by sampling weights (giving same weight to each municipality). Least squares estimations with variables aggregated at the municipality level in Columns (1)–(4); two-stage least squares estimations in Columns (5)–(8). Sample: West German employees aged 20–65 years, no first-generation immigrants. "No own MDF sample" includes only municipalities without an own main distribution frame (MDF). ICT skills are standardized to SD 1 within Germany. *Threshold:* binary variable indicating whether a municipality is more than 4,200 meters away from its MDF (1 = lower probability of DSL availability), and 0 otherwise. Distance calculations are based on municipalities' geographic centroid. *Unemployment rate in 1999:* municipality-level share of unemployed individuals in the working-age population (18–65 years), measured in 1999 (i.e., before the emergence of broadband Internet in Germany in 2000). *Population share 65+ in 1999:* municipality-level population share of individuals older than 65 years, measured in 1999. *Experience:* years of actual work experience. Robust standard errors, adjusted for clustering at the municipality level, in parentheses. Significance levels: * $p<0.10$, ** $p<0.05$, *** $p<0.01$. *Data sources:* German Broadband Atlas, German Federal Statistical Office, PIAAC.

Table 3: Mechanisms: Occupational Selection (International Evidence)

| | Occupational task content | | | |
|---|---|---|---|---|
| | Abstract | Routine | Manual | Computer use |
| | (1) | (2) | (3) | (4) |
| Second stage | | | | |
| ICT skills | 0.803*** | –0.406** | –0.343** | 0.540*** |
| | (0.180) | (0.179) | (0.148) | (0.111) |
| Age 20–34 | –0.925*** | 0.477*** | 0.424*** | –0.578*** |
| | (0.156) | (0.155) | (0.128) | (0.096) |
| Age 35–44 | –0.565*** | 0.336*** | 0.287*** | –0.341*** |
| | (0.120) | (0.119) | (0.098) | (0.073) |
| Age 45–54 | –0.286*** | 0.154*** | 0.151*** | –0.180*** |
| | (0.059) | (0.059) | (0.048) | (0.036) |
| Female | 0.139*** | –0.297*** | –0.493*** | –0.012 |
| | (0.022) | (0.022) | (0.018) | (0.014) |
| Country fixed effects | X | X | X | X |
| First stage (Dependent variable: ICT skills) | | | | |
| Fixed-line diffusion × age 20–34 | 0.398** | 0.398** | 0.398** | 0.398** |
| | (0.155) | (0.155) | (0.155) | (0.155) |
| Fixed-line diffusion × age 35–44 | 0.840*** | 0.840*** | 0.840*** | 0.841*** |
| | (0.168) | (0.168) | (0.168) | (0.168) |
| Fixed-line diffusion × age 45–54 | 0.261 | 0.261 | 0.261 | 0.256 |
| | (0.170) | (0.170) | (0.170) | (0.170) |
| Cragg-Donald Wald F statistic | 27.9 | 27.9 | 27.9 | 28.2 |
| Stock & Yogo critical value | 9.1 | 9.1 | 9.1 | 9.1 |
| Individuals | 53,132 | 53,132 | 53,132 | 53,110 |
| ø wage in occ. with "high" task content | 19.9 | 17.0 | 16.3 | 20.2 |

*Notes:* Two-stage least squares regressions weighted by sampling weights (giving same weight to each country). Sample: employees aged 20–65 years, no first-generation immigrants; individuals who did not provide information on their occupation are also excluded. Task measures in Columns (1)–(3) are taken from Goos et al. (2014). The abstract task measure is the average of two variables from the U.S. Dictionary of Occupational Titles (DOT): "direction control and planning," measuring managerial and interactive tasks, and "GED Math," measuring mathematical and formal reasoning requirements; the routine task measure is a simple average of two DOT variables, "set limits, tolerances and standards," measuring an occupation's demand for routine cognitive tasks, and "finger dexterity," measuring an occupation's use of routine motor tasks; and the manual task measure corresponds to the DOT variable measuring an occupation's demand for "eye-hand-foot coordination." The task measures are mapped onto the ISCO occupational classification system (two-digit level) and are normalized to have mean 0 and SD 1 across occupations (Goos et al., 2014). Computer use index is based on questions indicating how often a person performs the following activities at work: create or read spreadsheets, use word-processing software, use programming language, and engage in computer-aided real-time discussions; answers are combined to a single index following the procedure described in Kling et al. (2007) and then aggregated to the country-occupation (two-digit ISCO) level. ICT skills are standardized to SD 1 across countries. *Fixed-line diffusion:* voice-telephony penetration rate (telephone access lines per inhabitant) in 1996. Omitted age category is 55–65 years. Robust standard errors in parentheses. Significance levels: * p<0.10, ** p<0.05, *** p<0.01. *Data sources:* Goos et al. (2014), ITU, PIAAC.

Table 4: Mechanisms: Occupational Selection (Within-Germany Evidence)

| Second stage (Dependent variable: occupational task content) | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | Full sample | | | | No own MDF sample | | | |
| | Abstract | Routine | Manual | Computer use | Abstract | Routine | Manual | Computer use |
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
| ICT skills | 0.420* | 0.346 | –0.397 | 0.466*** | 0.989*** | –0.454* | –0.637** | 0.556*** |
| | (0.236) | (0.220) | (0.285) | (0.166) | (0.233) | (0.274) | (0.300) | (0.148) |
| Municipality characteristics | X | X | X | X | X | X | X | X |
| Individual characteristics | X | X | X | X | X | X | X | X |
| First stage (Dependent variable: ICT skills) | | | | | | | | |
| Threshold | –0.372*** | –0.372*** | –0.372*** | –0.371*** | –0.512*** | –0.512*** | –0.512*** | –0.517*** |
| | (0.116) | (0.116) | (0.116) | (0.114) | (0.154) | (0.154) | (0.154) | (0.153) |
| Kleibergen-Paap F statistic | 10.3 | 10.3 | 10.3 | 10.6 | 11.0 | 11.0 | 11.0 | 11.5 |
| Individuals | 1,810 | 1,810 | 1,810 | 1,834 | 158 | 158 | 158 | 160 |
| Municipalities | 204 | 204 | 204 | 204 | 18 | 18 | 18 | 18 |
| ø wage in occ. with "high" task content | 18.5 | 15.5 | 13.8 | 19.3 | 18.7 | 15.3 | 12.8 | 20.4 |

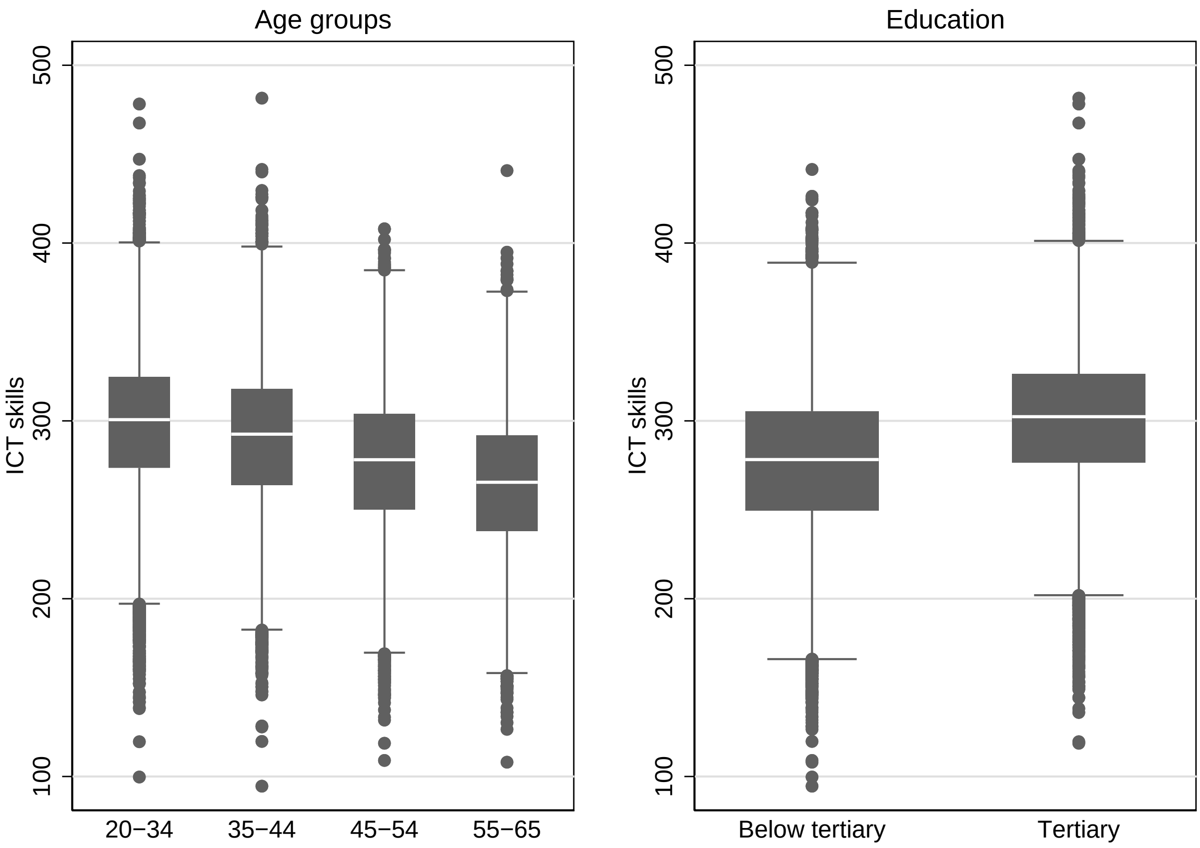
*Notes:* Two-stage least squares regressions weighted by sampling weights (giving same weight to each municipality). Sample: West German employees aged 20–65 years, no first-generation immigrants; individuals who did not provide information on their occupation are also excluded. Columns (1)–(4) show results for all West German municipalities in the sample; Columns (5)–(8) restrict the sample to West German municipalities without an own main distribution frame (MDF). Task measures are taken from Goos et al. (2014). The abstract task measure is the average of two variables from the U.S. Dictionary of Occupational Titles (DOT): "direction control and planning" measuring managerial and interactive tasks, and "GED Math," measuring mathematical and formal reasoning requirements; the routine task measure is a simple average of two DOT variables, "set limits, tolerances and standards," measuring an occupation's demand for routine cognitive tasks, and "finger dexterity," measuring an occupation's use of routine motor tasks; and the manual task measure corresponds to the DOT variable measuring an occupation's demand for "eye-hand-foot coordination." The task measures are mapped onto the ISCO occupational classification system (two-digit level) and are normalized to have mean 0 and SD 1 across occupations (Goos et al., 2014). Computer use index is based on questions indicating how often a person performs the following activities at work: create or read spreadsheets, use word-processing software, use programming language, and engage in computer-aided real-time discussions; answers are combined to a single index following the procedure described in Kling et al. (2007) and then aggregated to the two-digit ISCO level. ICT skills are standardized to SD 1 within Germany. *Threshold:* binary variable equal to 1 if a municipality is more than 4,200 meters away from its MDF (lower probability of DSL availability), and 0 otherwise. Distance calculations are based on municipalities' geographic centroid. Municipality characteristics are unemployment rate in 1999 (i.e., share of unemployed individuals in the working-age population aged 18-–65 years) and population share of individuals older than 65 in 1999. Individual characteristics are a quadratic polynomial in work experience and gender. Robust standard errors, adjusted for clustering at the municipality level, in parentheses. Significance levels: * $p<0.10$, ** $p<0.05$, *** $p<0.01$.
*Data sources:* German Broadband Atlas, German Federal Statistical Office, PIAAC.

# Returns to ICT Skills –
# Online Appendix (Not for Publication)

Oliver Falck, Alexandra Heimisch-Roecker, Simon Wiederhold

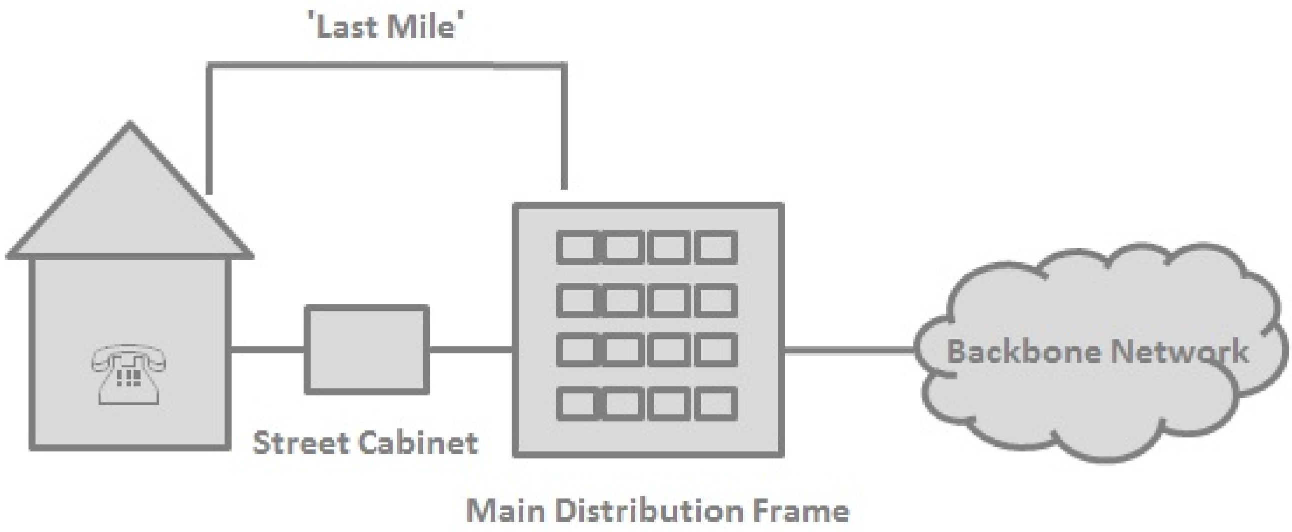
# Online Appendix A: Further Results

Figure A-1: ICT Skills by Age and Education



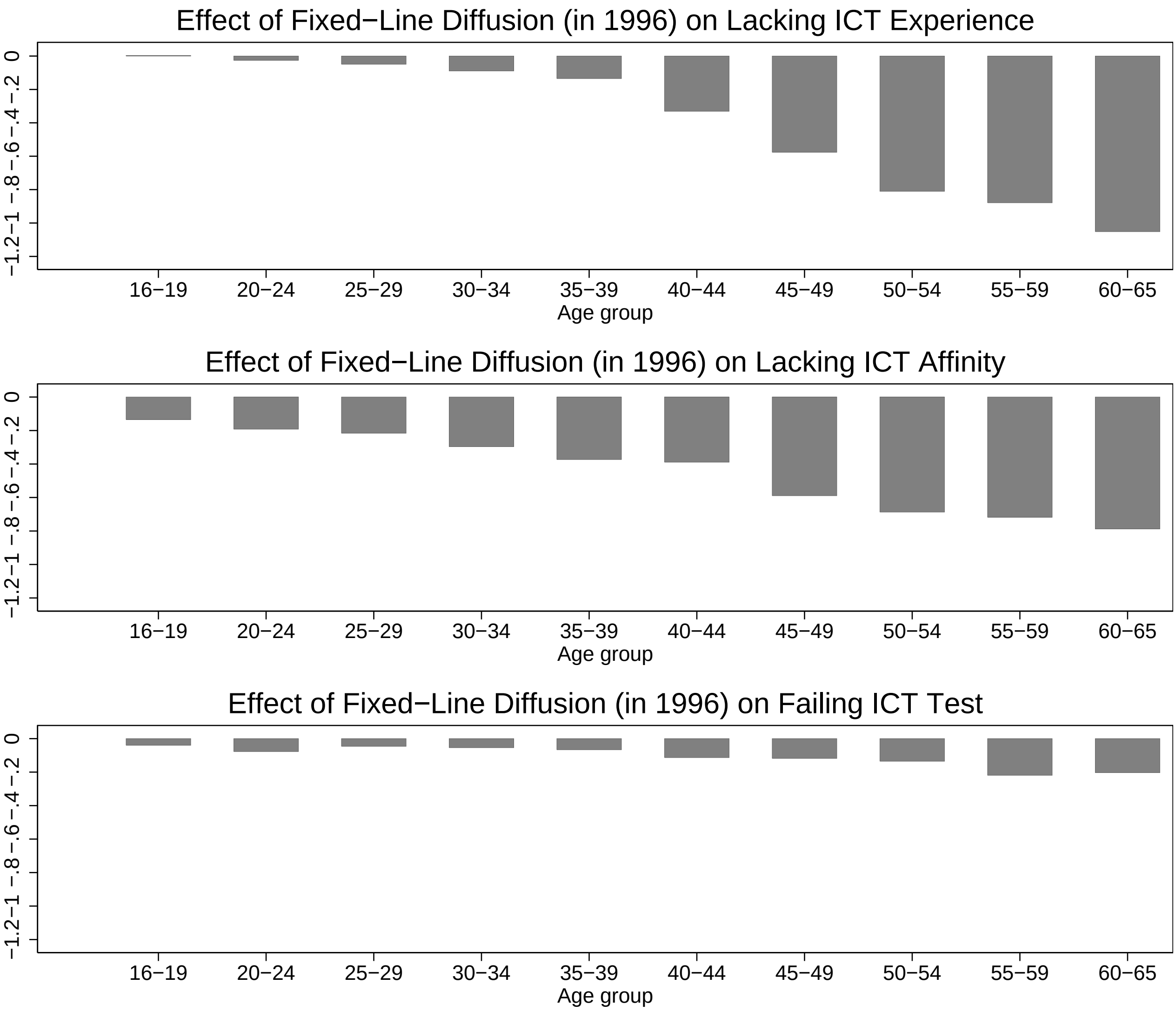

*Notes:* Graph shows box plots of ICT skills for indicated age groups and by educational attainment. Sample: employees aged 20–65 years, no first-generation immigrants. *Data source:* PIAAC.

Figure A-2: The Structure of a DSL Network



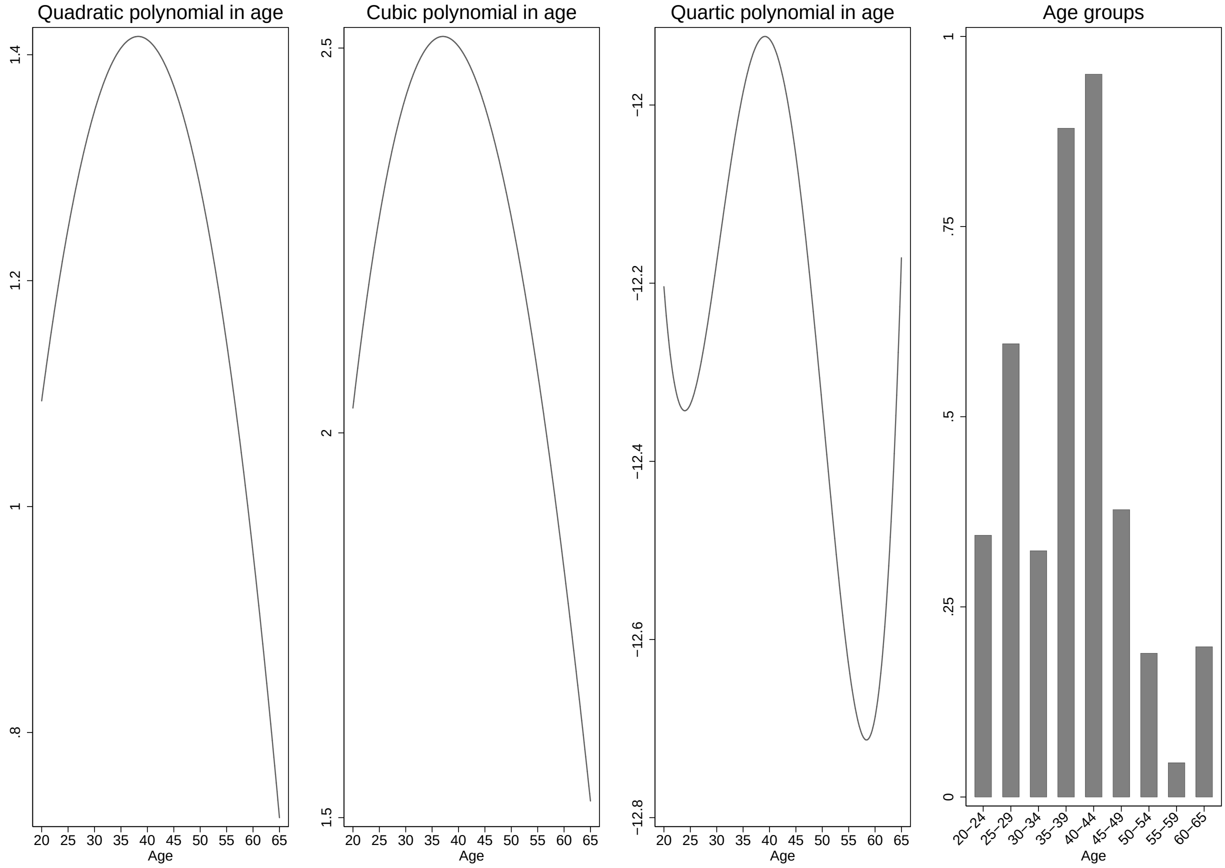

*Notes:* The figure shows the structure of a DSL network that relies on the "last mile" of the preexisting fixed-line voice-telephony network. The "last mile" consists of copper wires connecting every household via the street cabinet to the main distribution frame. At the main distribution frame, a DSLAM (Digital Subscription Line Access Multiplexer) is installed that aggregates and redirects the voice and data traffic to the telecommunication operator's backbone network.

Figure A-3: Preexisting Fixed-Line Diffusion and ICT Illiteracy by Age Group



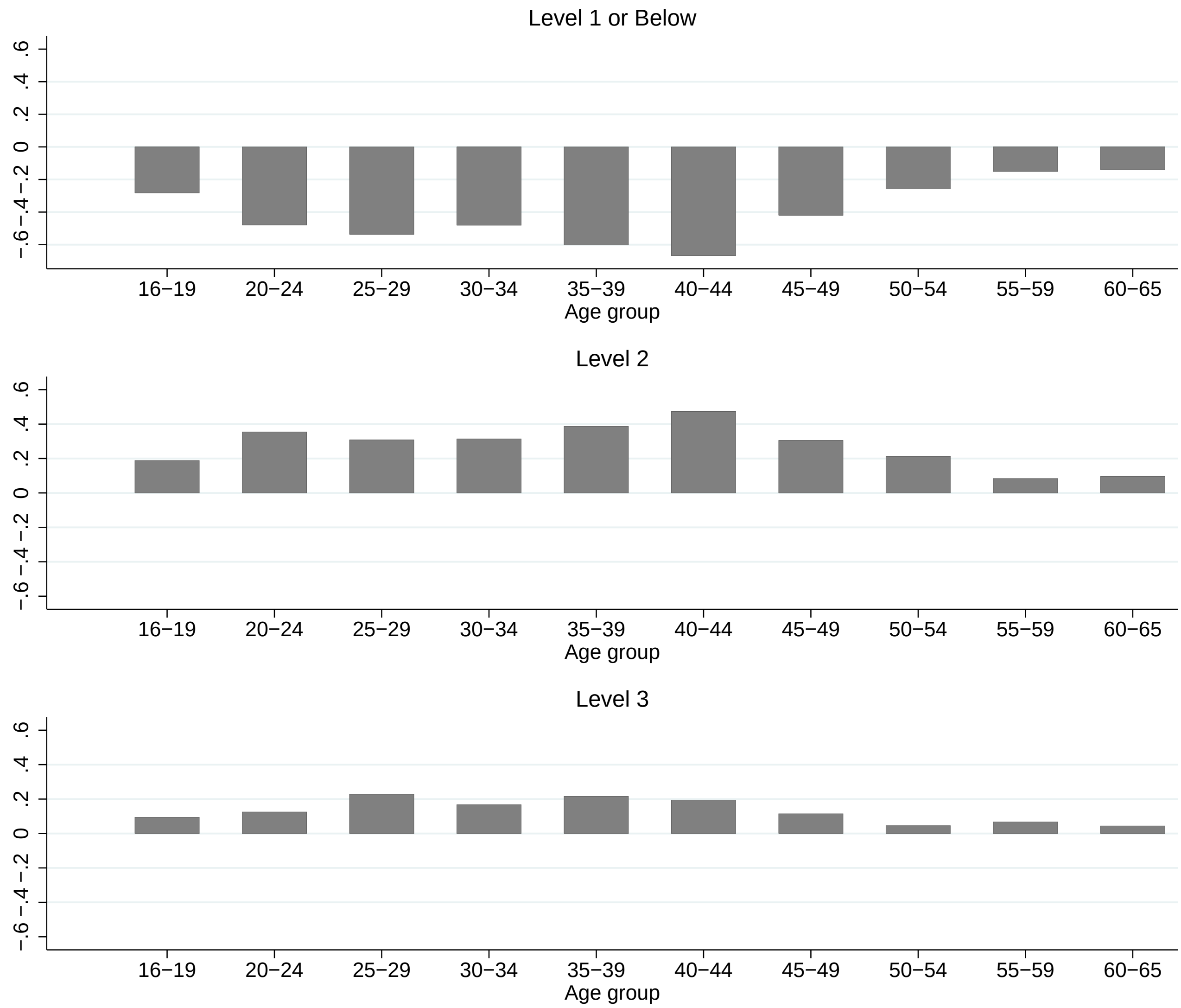

*Notes:* Coefficient estimates on fixed-line voice-telephony diffusion (in 1996) for indicated age groups in a regression of ICT illiteracy on fixed-line diffusion, by reason for ICT illiteracy. ICT skills can be missing in PIAAC due to lack of computer experience reported by the respondent (Panel A), opting out of the computer-based assessment (Panel B), or failing an initial ICT core test (Panel C). ICT illiteracy is measured as the share of PIAAC respondents with missing ICT skills (due to any of the above reasons) in PIAAC respondents with non-missing ICT skills. Regression weighted by sampling weights (giving same weight to each country). Sample: employees, no first-generation immigrants. Fixed-line diffusion is the voice-telephony penetration rate (telephone access lines per inhabitant) in 1996. *Data sources:* ITU, PIAAC.

Figure A-4: The Impact of Fixed-Line Diffusion on ICT Skills by Age: Functional Forms



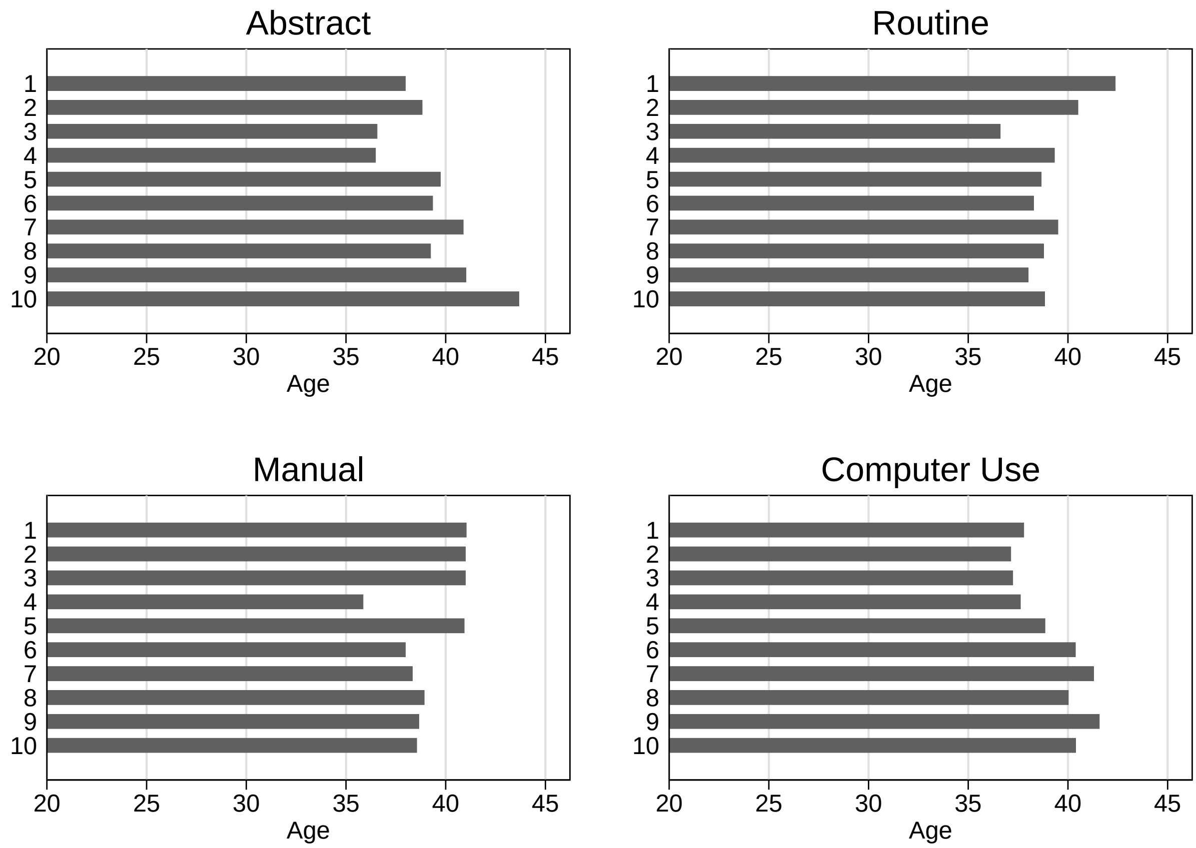

*Notes:* Coefficient estimates on fixed-line diffusion (in 1996) interacted with various functional forms of age (indicated in the panel heading) in a regression of ICT skills (standardized to SD 1 across countries) on fixed-line-diffusion-age interactions, respective age variables, gender, and country fixed effects. In the very right panel, omitted age category is 16–19 years. Regression weighted by sampling weights (giving same weight to each country). Sample: employees aged 20–65 years, no first-generation immigrants. Fixed-line diffusion is the voice-telephony penetration rate (telephone access lines per inhabitant) in 1996. *Data sources:* ITU, PIAAC.

Figure A-5: Preexisting Fixed-Line Diffusion and ICT-Proficiency Level by Age Group



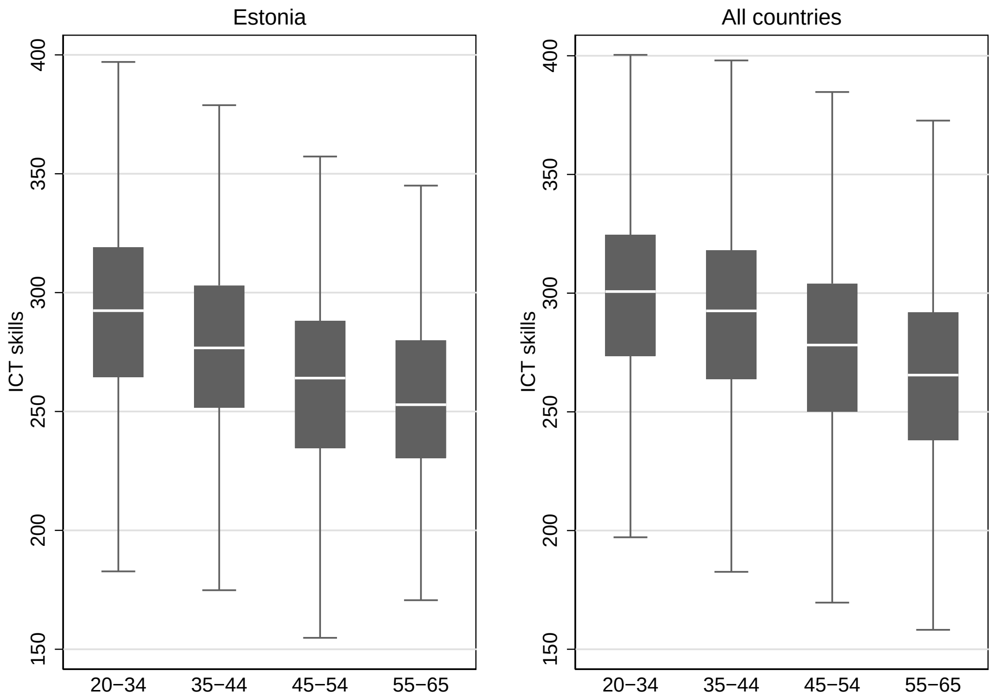

*Notes:* Coefficient estimates on fixed-line voice-telephony diffusion (in 1996) for indicated age groups in a regression of ICT proficiency on fixed-line diffusion. ICT proficiency is a binary variable indicating whether a person has the ICT proficiency level mentioned in the panel header, and 0 otherwise: level 1 or below = less than 291 PIAAC points; level 2 = 291–340 points; level 3 = more than 340 points (OECD, 2013a). All regressions control for gender and are weighted by sampling weights (giving same weight to each country). Sample: employees, no first-generation immigrants. *Data sources:* ITU, PIAAC.

Figure A-6: Age Composition of Job Tasks



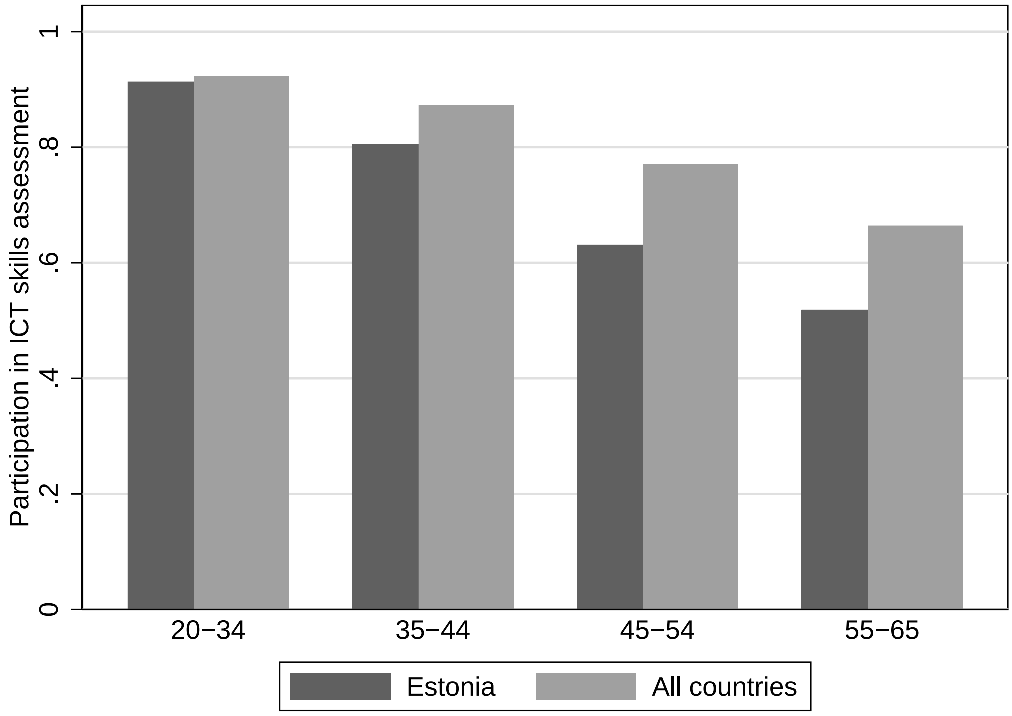

*Notes:* Graph shows the average age of employees working in jobs at the 1st to 10th decile in the distribution of abstract, routine, manual, and computer-intensive tasks, respectively. Sample: employees aged 20–65 years, no first-generation immigrants; individuals who did not provide information on their occupation are also excluded. Measures of abstract, routine, and manual tasks are taken from Goos et al. (2014). The abstract task measure is the average of two variables from the U.S. Dictionary of Occupational Titles (DOT): "direction control and planning," measuring managerial and interactive tasks, and "GED Math," measuring mathematical and formal reasoning; the routine task measure is a simple average of two DOT variables, "set limits, tolerances and standards," measuring an occupation's demand for routine cognitive tasks, and "finger dexterity," measuring an occupation's use of routine motor tasks; and the manual task measure corresponds to the DOT variable measuring an occupation's demand for "eye-hand-foot coordination." The task measures are mapped onto the ISCO occupational classification system (two-digit level); see Goos et al. (2014). Computer use index is based on questions indicating how often a person performs the following activities at work: create or read spreadsheets, use word-processing software, use programming language, and engage in computer-aided real-time discussions; answers are combined to a single index following the procedure described in Kling et al. (2007) and then aggregated to the country-occupation (two-digit ISCO) level. *Data sources:* Goos et al. (2014), PIAAC.

Figure A-7: ICT Skills by Age: Estonia vs. International




*Notes:* Graph shows box plots of ICT skills for indicated age groups in Estonia (left figure) and in the full sample (right figure). Sample: employees aged 20–65 years, no first-generation immigrants. *Data source:* PIAAC.

Figure A-8: Participation in ICT Skills Assessment by Age: Estonia vs. International




*Notes:* Graph shows participation in the ICT skills assessment in Estonia vs. the full sample. Non-participation in the assessment can occur due to lack of computer experience reported by the respondent, opting out of the computer-based assessment, or failing an initial ICT core test. Sample: employees aged 20–65 years, no first-generation immigrants. *Data source:* PIAAC.

Table A-1: Descriptive Statistics

| | Pooled | Australia | Austria | Belgium | Canada | Czech R. | Denmark | Estonia | Finland | Germany |
|---|---|---|---|---|---|---|---|---|---|---|
| Gross hourly wage | 18.0 | 19.2 | 17.0 | 20.3 | 20.7 | 9.2 | 24.3 | 10.4 | 18.8 | 19.2 |
| (in PPP-USD) | (10.2) | (8.7) | (6.6) | (7.3) | (9.4) | (4.2) | (8.3) | (6.3) | (6.9) | (9.5) |
| ICT skills | 287.3 | 293.7 | 286.9 | 284.4 | 287.4 | 282.8 | 287.6 | 277.8 | 294.3 | 288.4 |
| | (41.3) | (37.5) | (37.1) | (41.6) | (42.8) | (44.1) | (40.2) | (41.7) | (41.3) | (41.4) |
| Numeracy skills | 287.8 | 284.6 | 290.6 | 294.4 | 282.0 | 285.8 | 293.2 | 284.2 | 298.6 | 288.2 |
| | (44.1) | (45.9) | (41.3) | (43.9) | (47.3) | (40.6) | (42.4) | (42.0) | (43.5) | (44.5) |
| Literacy skills | 288.8 | 294.1 | 281.9 | 289.2 | 288.9 | 280.6 | 284.2 | 284.1 | 302.0 | 282.5 |
| | (40.7) | (41.0) | (37.8) | (40.6) | (43.7) | (39.7) | (38.5) | (41.9) | (42.5) | (42.4) |
| Experience (years) | 18.0 | 18.4 | 18.7 | 19.3 | 20.3 | 17.2 | 22.4 | 15.9 | 17.9 | 19.0 |
| | (11.5) | (11.3) | (10.8) | (11.0) | (11.5) | (11.0) | (11.9) | (11.1) | (11.6) | (12.0) |
| Female (share) | 0.49 | 0.49 | 0.50 | 0.48 | 0.49 | 0.44 | 0.50 | 0.56 | 0.52 | 0.48 |
| Observations | 53,879 | 2,533 | 2,061 | 2,267 | 10,499 | 1,959 | 3,296 | 2,626 | 2,770 | 2,517 |

| | Ireland | Japan | Korea | Netherl. | Norway | Poland | Slovak R. | Sweden | U.K. | U.S. |
|---|---|---|---|---|---|---|---|---|---|---|
| Gross hourly wage | 22.9 | 16.6 | 17.8 | 20.8 | 25.2 | 9.6 | 9.1 | 18.6 | 19.0 | 22.6 |
| (in PPP-USD) | (11.7) | (10.7) | (14.2) | (8.9) | (8.7) | (5.5) | (6.3) | (5.3) | (11.2) | (13.1) |
| ICT skills | 280.7 | 298.9 | 285.6 | 294.3 | 291.4 | 272.5 | 283.0 | 295.3 | 289.6 | 285.2 |
| | (38.9) | (44.1) | (36.0) | (38.2) | (38.5) | (47.8) | (37.4) | (40.9) | (40.8) | (43.9) |
| Numeracy skills | 274.6 | 301.6 | 278.6 | 294.1 | 295.8 | 276.4 | 292.8 | 296.2 | 282.5 | 273.1 |
| | (44.9) | (40.3) | (37.1) | (42.3) | (44.0) | (43.6) | (37.9) | (43.2) | (46.2) | (49.6) |
| Literacy skills | 283.2 | 306.0 | 283.8 | 297.9 | 291.5 | 281.0 | 285.2 | 295.5 | 288.0 | 287.1 |
| | (41.6) | (35.5) | (35.0) | (40.5) | (38.9) | (42.3) | (33.6) | (38.9) | (42.5) | (43.4) |
| Experience (years) | 16.7 | 17.2 | 11.6 | 19.0 | 19.8 | 13.1 | 16.0 | 19.9 | 19.8 | 20.7 |
| | (10.2) | (10.8) | (8.8) | (11.1) | (11.5) | (10.4) | (10.7) | (12.6) | (11.5) | (12.0) |
| Female (share) | 0.56 | 0.39 | 0.42 | 0.48 | 0.50 | 0.48 | 0.49 | 0.49 | 0.49 | 0.52 |
| Observations | 1,738 | 2,141 | 2,203 | 2,575 | 2,746 | 2,503 | 1,649 | 2,351 | 3,572 | 1,873 |

*Notes:* Means, SDs (in parentheses), and number of observations for selected variables by country. Sample: employees aged 20–65 years, no first-generation immigrants. Pooled specification gives same weight to each country. *Data source:* PIAAC.

Table A-2: Returns to ICT Skills: Clustered Standard Errors

| Dependent variable: log gross hourly wage | | | |
|---|---|---|---|
| Cluster level: | Country | Country times age brackets | Country times age cont. |
| | (1) | (2) | (3) |
| ICT skills | 0.236** | 0.236 | 0.236** |
| | (0.118) | (0.146) | (0.094) |
| | [0.064] | [0.117] | [0.002] |
| Age 20–34 | –0.457*** | –0.457*** | –0.457*** |
| | (0.118) | (0.131) | (0.085) |
| Age 35–44 | –0.191** | –0.191* | –0.191*** |
| | (0.084) | (0.101) | (0.064) |
| Age 45–54 | –0.086** | –0.086* | –0.086*** |
| | (0.039) | (0.051) | (0.032) |
| Female | –0.148*** | –0.148*** | –0.148*** |
| | (0.031) | (0.022) | (0.012) |
| Country fixed effects | X | X | X |
| First stage (Dependent variable: ICT skills) | | | |
| Fixed-line diffusion × age 20–34 | 0.384 | 0.384 | 0.384* |
| | (0.330) | (0.256) | (0.216) |
| Fixed-line diffusion × age 35–44 | 0.839*** | 0.839*** | 0.839*** |
| | (0.284) | (0.246) | (0.227) |
| Fixed-line diffusion × age 45–54 | 0.253 | 0.253 | 0.253 |
| Individuals | 53,879 | 53,879 | 53,879 |

*Notes:* Regressions weighted by sampling weights (giving same weight to each country). Two-stage least squares estimations. Sample: employees aged 20–65 years, no first-generation immigrants. Dependent variable in second stage, *log gross hourly wage*, is measured in PPP-USD. ICT skills are standardized to SD 1 across countries. *Fixed-line diffusion:* voice-telephony penetration rate (telephone access lines per inhabitant) in 1996. Omitted age category is 55–65 years. Standard errors are clustered at the level indicated in the column header; age groups are ages 20–34, 35–44, 45–54, and 55–65 years. Value in square brackets below standard errors on ICT skills coefficients reports p-value from wild bootstrap (Anderson-Rubin test, wild restricted efficient bootstrap (WRE), Rademacher weights, 999 replications); implemented using Stata' `boottest` command. Number of clusters: 19 in Column (1), 76 in Column (2), 762 in Column (3). Significance levels: * p<0.10, ** p<0.05, *** p<0.01. *Data sources:* ITU, PIAAC.

Table A-3: International Evidence: First Stage

| Dependent variable: ICT skills | (3) | (4) |
|---|---|---|
| Fixed-line diffusion | 0.554*** | |
| | (0.141) | |
| Fixed-line diffusion × age 20–34 | 0.505*** | 0.384** |
| | (0.155) | (0.155) |
| Fixed-line diffusion × age 35–44 | 0.920*** | 0.839*** |
| | (0.169) | (0.168) |
| Fixed-line diffusion × age 45–54 | 0.288* | 0.253 |
| | (0.171) | (0.170) |
| Age 20–34 | 0.841*** | 0.848*** |
| | (0.017) | (0.017) |
| Age 35–44 | 0.643*** | 0.646*** |
| | (0.017) | (0.017) |
| Age 45–54 | 0.297*** | 0.301*** |
| | (0.018) | (0.018) |
| Female | –0.120*** | –0.112*** |
| | (0.010) | (0.010) |
| Country fixed effects | | X |
| Individuals | 53,879 | 53,879 |

*Notes:* Table shows first-stage results of Table 1, Columns (3) and (4). Least squares regressions weighted by sampling weights (giving same weight to each country). Sample: employees aged 20–65 years, no first-generation immigrants. ICT skills are standardized to SD 1 across countries. *Fixed-line diffusion:* voice-telephony penetration rate (telephone access lines per inhabitant) in 1996. Fixed-line diffusion is demeaned. Omitted age category is 55–65 years. Robust standard errors in parentheses. Significance levels: * $p<0.10$, ** $p<0.05$, *** $p<0.01$. *Data sources:* ITU, PIAAC.

Table A-4: Complier Analysis

| Dependent variable is indicated in the column header | | Occupational task content | | |
|---|---|---|---|---|
| | Wage | Abstract | Routine | Manual |
| | (1) | (2) | (3) | (4) |
| ICT skills | 0.127*** | 0.351*** | –0.157*** | –0.224*** |
| | (0.011) | (0.024) | (0.025) | (0.021) |
| × level 1 or below | –0.013 | –0.073*** | 0.088*** | 0.021 |
| | (0.013) | (0.027) | (0.028) | (0.023) |
| × level 3 | –0.086*** | –0.234*** | 0.160*** | 0.199*** |
| | (0.024) | (0.051) | (0.053) | (0.040) |
| Level 1 or below | –0.032 | –0.175*** | 0.163** | 0.155*** |
| | (0.026) | (0.060) | (0.064) | (0.056) |
| Level 3 | 0.117* | 0.258* | –0.160 | –0.246** |
| | (0.062) | (0.133) | (0.133) | (0.097) |
| Individual Characteristics | X | X | X | X |
| Country fixed effects | X | X | X | X |
| Interactions with ICT-proficiency level | X | X | X | X |
| R squared | 0.46 | 0.13 | 0.05 | 0.13 |
| Individuals | 53,879 | 53,132 | 53,132 | 53,132 |

*Notes:* Least squares regressions weighted by sampling weights (giving same weight to each country). Sample: employees aged 20–65 years, no first-generation immigrants (in Columns (2)–(4), individuals who did not provide information on their occupation are excluded). Dependent variable is the logarithm of gross hourly wage (in PPP-USD) in Column (1) and task measures taken from Goos et al. (2014) in Columns (2)–(4). The abstract task measure is the average of two variables from the U.S. Dictionary of Occupational Titles (DOT): "direction control and planning," measuring managerial and interactive tasks, and "GED Math," measuring mathematical and formal reasoning requirements; the routine task measure is a simple average of two DOT variables, "set limits, tolerances and standards," measuring an occupations demand for routine cognitive tasks, and "finger dexterity," measuring an occupations use of routine motor tasks; and the manual task measure corresponds to the DOT variable measuring an occupations demand for "eye-hand-foot coordination." The task measures are mapped onto the ISCO occupational classification system (two-digit level) and are normalized to have mean 0 and SD 1 across occupations (see also Tables 3 and 4). *Level* refers to the level of ICT proficiency achieved by the individual: level 1 or below = less than 291 PIAAC points; level 2 = 291–340 points; level 3 = more than 340 points (OECD, 2013a). Omitted category is ICT-proficiency level 2. All regressions control for age cohorts, gender, country fixed effects, and interactions of the covariates with the ICT-proficiency level. ICT skills are standardized to SD 1 across countries. Robust standard errors in parentheses. Significance levels: * $p<0.10$, ** $p<0.05$, *** $p<0.01$. *Data sources:* Goos et al. (2014), ITU, PIAAC.

Table A-5: Within-Germany Evidence: First Stage

| Dependent variable: log gross hourly wage | Full sample | | No own MDF sample | |
|---|---|---|---|---|
| | (5) | (6) | (7) | (8) |
| Threshold | –0.404*** | –0.369*** | –0.592*** | –0.517*** |
| | (0.102) | (0.114) | (0.126) | (0.153) |
| Unemployment rate in 1999 | –2.152 | –2.582** | –0.986 | 1.073 |
| | (1.376) | (1.261) | (3.846) | (5.448) |
| Population share 65+ in 1999 | –0.837 | –0.886 | –5.126* | –6.941** |
| | (1.312) | (1.253) | (2.650) | (2.602) |
| Experience | | –0.004 | | –0.004 |
| | | (0.007) | | (0.025) |
| Experience$^2$ (/100) | | –0.052*** | | –0.070 |
| | | (0.016) | | (0.053) |
| Female | | –0.149*** | | –0.292* |
| | | (0.046) | | (0.145) |
| Individuals | 1,849 | 1,849 | 160 | 160 |
| Municipalities | 204 | 204 | 18 | 18 |

*Notes:* Table shows first-stage results of Table 2, Columns (5)–(8). Least squares regressions weighted by sampling weights (giving same weight to each municipality). Sample: West German employees aged 20–65 years, no first-generation immigrants. "No own MDF sample" includes only municipalities without an own main distribution frame (MDF). ICT skills are standardized to SD 1 within Germany. *Threshold:* binary variable equal to 1 if a municipality is more than 4,200 meters away from its MDF (lower probability of DSL availability), and 0 otherwise. Distance calculations are based on municipalities' geographic centroid. *Unemployment rate in 1999:* municipality-level share of unemployed individuals in the working-age population (18–65 years). *Population share 65+ in 1999:* municipality-level population share of individuals older than 65 years. *Experience:* years of actual work experience. Robust standard errors, adjusted for clustering at the municipality level, in parentheses. Significance levels: * p<0.10, ** p<0.05, *** p<0.01. *Data sources:* German Broadband Atlas, German Federal Statistical Office, PIAAC.

Table A-6: Training and (ICT) Skills

| Dependent variable: ICT skills | Age group 20–34 | | | Age group 35–44 | | | Age group 45–55 | | | Age group 55–65 | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | ICT | Lit | Num | ICT | Lit | Num | ICT | Lit | Num | ICT | Lit | Num |
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) | (10) | (11) | (12) |
| Any training | 0.318*** | 0.319*** | 0.274*** | 0.378*** | 0.372*** | 0.332*** | 0.347*** | 0.376*** | 0.318*** | 0.297*** | 0.347*** | 0.311*** |
| | (0.017) | (0.017) | (0.017) | (0.022) | (0.021) | (0.020) | (0.022) | (0.022) | (0.021) | (0.030) | (0.028) | (0.028) |
| Female | –0.034** | 0.030* | –0.179*** | –0.157*** | –0.093*** | –0.275*** | –0.157*** | –0.106*** | –0.302*** | –0.203*** | –0.180*** | –0.376*** |
| | (0.016) | (0.016) | (0.015) | (0.020) | (0.019) | (0.018) | (0.021) | (0.020) | (0.019) | (0.028) | (0.027) | (0.026) |
| Country fixed effects | X | X | X | X | X | X | X | X | X | X | X | X |
| Age (5-year-group) fixed effects | X | X | X | X | X | X | X | X | X | X | X | X |
| Participation in any training | 0.648 | 0.648 | 0.648 | 0.684 | 0.684 | 0.684 | 0.691 | 0.691 | 0.691 | 0.656 | 0.656 | 0.656 |
| Individuals | 20,294 | 20,294 | 20,294 | 13,753 | 13,753 | 13,753 | 12,423 | 12,423 | 12,423 | 7,393 | 7,393 | 7,393 |

*Notes:* Least squares regressions weighted by sampling weights (giving same weight to each country). Sample: employees, no first-generation immigrants, age group indicated in the column header. ICT, literacy, and numeracy skills are standardized to SD 1 across countries. *Any training* indicates at least one participation in the previous year in on-the-job training, seminars/workshops, open/distance education, or private lessons. *Participation in any training*, reported in the bottom of the table, indicates average participation in training in the respective age group. Robust standard errors in parentheses. Significance levels: * $p<0.10$, ** $p<0.05$, *** $p<0.01$.
*Data sources:* ITU, PIAAC.

## Online Appendix B: Measurement Error

Like in any performance assessment, ICT skills in PIAAC are likely an error-ridden measure of a person's true ICT skills. As is well known, measurement error in the explanatory variable may lead to a downward bias in the estimated coefficient. We now assess the importance of measurement error for our estimates and propose two ways of correcting the corresponding attenuation bias.

We begin our analysis by assuming that ICT skills are measured with random noise. Let $ICT^*$ denote the true ICT skills of a person (suppressing person and country indices for convenience) and let the observed ICT skills be denoted by $ICT = ICT^* + u$. Here, $u$ is the measurement error, assumed to have mean zero and to be uncorrelated with $ICT^*$ (classical measurement error). In a bivariate model, the true effect of ICT skills on wages, $w$, will then be asymptotically biased towards zero:

$$\log w = \beta \lambda ICT + \varepsilon,$$

where $\lambda = \frac{Var(ICT^*)}{Var(ICT^*)+Var(u)}$. The factor $\lambda$ indicates how much the true effect $\beta$ is attenuated and is often referred to as the reliability ratio or signal-to-noise ratio. Neffke (2019) shows that in this classical errors-in-variables model the estimated coefficient on ICT skills, $\hat{\beta}$, can be written as:

$$\hat{\beta} = \beta \left(1 - \frac{Var(u)}{Var(ICT)}\right),$$

that is, the downward bias is the ratio of the variance of the measurement error to the total variance (including the measurement error) of ICT skills.

In a multivariate model, measurement error bias will usually be exacerbated compared to the bivariate case. The intuition behind this is that the control variables explain part of $ICT^*$, but not of $u$. As a consequence, $Var(ICT|\boldsymbol{X}) < Var(ICT)$, but $Var(u)$ remains the same (see also Griliches and Hausman, 1986). To calculate $Var(ICT|\boldsymbol{X})$, one has to regress $ICT$ on all other covariates and then use the variance of the residuals of this regression instead of $Var(ICT)$ in the denominator of the bias term above.

In light of this discussion, there are two ways to adjust the estimated coefficient on ICT skills for measurement error. One way is to obtain information on $Var(u)$, the other is to use two different measures of ICT skills (with uncorrelated measurement errors).

***Bias adjustment using $Var(u)$.*** To back out a measure of $Var(u)$, we use information on ICT test reliability published in the Technical Report of PIAAC (OECD, 2013b). Test reliability is computed by calculating how much variance in ICT skills is explained by the item responses and background factors included in the model to derive the skill values.[1] The reliability ratios were estimated for each country separately depending on the country-specific distributions for ICT skills (the procedure was similar for numeracy and literacy skills).[2] The country-specific reliability ratios range from 0.8 (in the Slovak Republic) to 0.89 (in Sweden), with a mean ratio of 0.85.[3]

In our analysis, we pursue a conservative approach and use the lowest available reliability ratio, that is, $\lambda = 0.8$. (An obvious alternative would be to use the mean ratio, which would lead to a somewhat smaller bias adjustment.) This leads to an attenuation factor of 0.6. Therefore, multiplying our baseline coefficient by the factor $1/0.6 = 1.67$ will provide the measurement-error-corrected estimate of the effect of ICT skills on wages. For our baseline OLS coefficient of 0.122, this implies a corrected effect of 0.203.

***Bias adjustment using different measures of ICT skills.*** Another way to correct for measurement error in the ICT-skills variable is to use multiple measures of ICT skills. Since we have both the answers and difficulty levels of all questions that were used to create the ICT-skill measure, we can split the assessment into two parts (each with the same average difficulty) and instrument ICT skills derived from one set of questions with ICT skills derived from the other set of questions. If measurement errors in both ICT-skill variables are uncorrelated, using one measure as an instrument for the other will remove part of the attenuation bias caused by measurement error.[4]

We first construct a sample of PIAAC participants that solved *all* ICT-related questions. As PIAAC also followed the common procedure in international assessment tests to administer different sets of items to different respondents, imposing this restriction reduces the sample to 8,791 respondents. We further divide the full set of questions into two parts, where each question

[1] As is typical in international assessments, test scores in PIAAC are a combination of an IRT (item response theory) model and a latent regression model. In the latent regression model, the distribution of proficiency is assumed to depend not only on the cognitive item responses but also on a number of predictors, obtained from the background questionnaire (e.g., gender, country of birth, education, etc.).

[2] See Chapter 18 in OECD (2013b) for details.

[3] In psychometric test theory, it is often argued that Cronbach's $\alpha$ is a natural indicator of test reliability. This measure is a function of the number of test items and the covariances between all possible item pairs. For instance, Bietenbeck et al. (2018) and Metzler and Woessmann (2012) use Cronbach's $\alpha$ to correct for measurement error in tested teacher subject knowledge. While Cronbach's $\alpha$ is not reported for any skill domain in PIAAC, it is possible to construct the measure by using respondents' answers to all individual test items (using Stata's *alpha* command). The estimated reliability ratio is 0.83 for the full sample, and ranges between 0.78 and 0.85 when estimated for each country separately. Thus, the estimated Cronbach's $\alpha$ is very similar to the reliability ratios reported by the OECD.

[4] Note that this approach does not solve measurement errors common to both ICT measures, for instance, when tested persons had a good or bad testing day. The above bias adjustment using the reliability ratio addresses this issue, however.

in one set has a twin question in the other set with the same difficulty level. We then estimate respondents' ICT skills on the basis of each set of questions. Specifically, separately for each set of questions, we regress the original ICT-skill measure in PIAAC on each question (coded as binary variables taking a value of 1 if the answer was correct and 0 otherwise)[5] and use the estimated coefficients to obtain predicted ICT skills.

Table B-1 summarizes the results of this approach. Column (1) repeats the OLS results of the baseline specification in Column (2) of Table 1 in the restricted sample containing only respondents who took all ICT-related questions. Reassuringly, returns to ICT skills are very similar as in the baseline. Column (2) shows that using predicted ICT skills from the first set of questions leads to almost identical returns as those estimated with the ICT-skill measure reported in PIAAC. In Column (3), we instrument ICT skills based on the first set of questions with ICT skills based on the second set of questions. The second measure is a very strong instrument for the first measure, with a point estimate of 0.72 and an F statistic of more than 6,800. In the second stage, the estimate on ICT skills increases by 47 percent, from 0.133 to 0.195. The results in Columns (4) and (5) indicate that results are very similar when we use ICT skills based on the second set of questions.[6]

Both adjustments address common concerns about test quality such as specific items on the ICT-skills test being a bad measure of skills relevant on the labor market (e.g., because ICT-based applications in the PIAAC test are substantially different from those needed at the workplace). The results show that taking away this measurement error leads to a substantial increase in estimated returns, suggesting that attenuation bias may indeed be an important issue in the analysis of returns to ICT skills. Importantly, these adjustments still understate the amount of error in our ICT-skills measure, because measurement error due the fact that test constructs developed in PIAAC may not be an encompassing measure of the underlying concept of ICT skills is not eliminated.

[5] Most questions in PIAAC were dichotomously scored. We collapsed questions that were originally polytomously scored, containing information also on "partly completing" and "almost completing" a question, into dichotomous answering categories to ensure comparability across questions. The correlation between the number of correctly solved questions and the ICT test score provided in PIAAC is 0.90.

[6] One potential issue arises from standardizing the ICT skills in Table B-1. When dividing raw ICT skills by its standard deviation, which equals $\sqrt{Var(ICT^*) + Var(u)}$, we also standardize $ICT^*$ with this denominator. Using IV to tackle measurement error assumes for the two measures of ICT skills that $ICT = \frac{ICT^*}{\sqrt{Var(ICT^*)}} + u$ , while we have $ICT = \frac{ICT^*}{\sqrt{Var(ICT^*)+Var(u)}} + u$ . To gauge the extent to which standardizing ICT skills affects the measurement-error correction, we redid the above analysis using non-standardized ICT skills. Reassuringly, the increase in the ICT skills coefficient after the measurement-error correction turned out to be very similar as in the case of standardized skills. For comparability with our baseline results, we thus prefer reporting the measurement-error correction with standardized ICT skills.

## Additional References


Bietenbeck, Jan, Marc Piopiunik, and Simon Wiederhold (2018): "Africa's Skill Tragedy: Does Teachers' Lack of Knowledge Lead to Low Student Performance?" *Journal of Human Resources* 53(3): 553–578.

Griliches, Zvi, and Jerry A. Hausman (1986): "Errors in variables in panel data." *Journal of Econometrics* 31(1): 93–118.

Metzler, Johannes, and Ludger Woessmann (2012): "The Impact of Teacher Subject Knowledge on Student Achievement: Evidence from Within-Teacher Within-Student Variation." *Journal of Development Economics*, 99: 486–496.

Neffke, Frank (2019): "The Value of Complementary Co-Workers." *Science Advances*, 5(12).

OECD (2013b): *Technical Report of the Survey of Adult Skills (PIAAC).* Paris: Organisation for Economic Co-operation and Development.

Table B-1: Measurement Error: Using a Second Measure of ICT Skills

| Dependent variable: log gross hourly wage | Baseline | ICT question set 1 | | ICT question set 2 | |
|---|---|---|---|---|---|
| | OLS | OLS | 2SLS | OLS | 2SLS |
| | (1) | (2) | (3) | (4) | (5) |
| ICT skills | 0.135*** | | | | |
| | (0.007) | | | | |
| ICT skills (question set 1) | | 0.133*** | 0.195*** | | |
| | | (0.008) | (0.011) | | |
| ICT skills (question set 2) | | | | 0.140*** | 0.187*** |
| | | | | (0.008) | (0.011) |
| Age 20–34 | –0.376*** | –0.357*** | –0.406*** | –0.348*** | –0.380*** |
| | (0.021) | (0.022) | (0.022) | (0.021) | (0.022) |
| Age 35–44 | –0.123*** | –0.106*** | –0.142*** | –0.105*** | –0.130*** |
| | (0.021) | (0.022) | (0.022) | (0.022) | (0.022) |
| Age 45–54 | –0.037* | –0.028 | –0.046** | –0.029 | –0.042* |
| | (0.021) | (0.022) | (0.022) | (0.022) | (0.021) |
| Female | –0.152*** | –0.155*** | –0.148*** | –0.156*** | –0.151*** |
| | (0.011) | (0.011) | (0.012) | (0.011) | (0.011) |
| Country fixed effects | X | X | X | X | X |
| First stage (Dependent variable: ICT skills) | | | | | |
| ICT skills (question set 2) | | | 0.720*** | | |
| | | | (0.009) | | |
| ICT skills (question set 1) | | | | | 0.709*** |
| | | | | | (0.009) |
| Cragg-Donald Wald F statistic | | | 6824.5 | | 6176.5 |
| Individuals | 8,791 | 8,791 | 8,791 | 8,791 | 8,791 |

*Notes:* Regressions weighted by sampling weights (giving same weight to each country). Least squares estimations in Columns (1), (2), and (4); two-stage least squares estimations in Columns (3) and (5). Sample: employees aged 20–65 years, no first-generation immigrants. Sample includes only respondents who answered all ICT-related questions. Dependent variable in second stage, *log gross hourly wage*, is measured in PPP-USD. All ICT skills measures are standardized to SD 1 across countries, using the SD from the full sample as numeraire. See text on the construction of ICT measures using only a subset of ICT-related questions. Omitted age category is 55–65 years. Robust standard errors in parentheses. Significance levels: * p<0.10, ** p<0.05, *** p<0.01. *Data source:* PIAAC.

## Online Appendix C: Assessing the Identification Strategy

### I. *Placebo Tests: Other Skill Domains and First-Generation Immigrants*

*International Analysis.* To interpret the IV results in Section 4 as showing a causal effect of ICT skills on wages (vis-à-vis a general ability effect), the age-induced variation in the impact of technologically determined broadband Internet availability has to isolate the effect of ICT skills on wages from that of other skills (e.g., DiNardo and Pischke, 1997). Thus, as a first placebo check, we replace ICT skills in the first-stage regression with numeracy and literacy skills, respectively, which are also available in the rich PIACC dataset. If our instruments do indeed isolate the effect of ICT skills, they should not be systematically related to numeracy and literacy skills. An analysis using numeracy or literacy skills as outcomes is preferable to controlling for these skills in the IV regressions because cognitive skills in PIAAC are measured simultaneously with wages and are thus endogenous.

Additionally, as detailed in Section 3.3, the technically determined availability of broadband Internet in a country should primarily affect the ICT skills of individuals who most likely used the Internet during this decade, not only when it comes to age, but also when it comes to location. Therefore, in a second placebo check we estimate the first-stage relationship by migration status. Although natives and second-generation immigrants most likely lived in the PIAAC test country during the first phase of extensive broadband diffusion in the early 2000s (which is likely to contribute most to the learning-by-doing effects we identify), almost 60 percent of first-generation immigrants in PIAAC had not yet migrated to the test country by 2000. We thus expect that the first-stage relationship is considerably weaker or even nonexistent for first-generation immigrants.

Table C-1 shows the results of these placebo tests. Conditional on ICT skills, we find that neither numeracy nor literacy skills are significantly related to the preexisting fixed-line network in our baseline sample of natives and second generation immigrants (Columns (1) and (2)).[1] However, there is still an inverted-U-shaped age pattern in the effect of the traditional fixed-line network on ICT skills when controlling for numeracy and literacy skills (Column (3)). Arguably, controlling for ICT skills is problematic because the instruments affect ICT skills, making it an endogenous variable in the numeracy and literacy regressions. However, results are very similar when we net out the effect of ICT skills on numeracy and literacy skills ex ante by using residualized skill scores

[1] As long as we do not control for ICT skills, the instruments show a similar (although less pronounced) age pattern for numeracy and literacy skills as for ICT skills, reflecting the high correlation between the different skill domains. Since the instruments lose predictive power for numeracy and literacy once we include ICT skills, preexisting fixed-line diffusion affects numeracy and literacy skills only through ICT skills.

(Columns (4) and (5)), and we continue to find a distinct age pattern for residualized ICT skills (Column (6)). However, the age pattern in Columns (3) and (6) of Table C-1 is somewhat weaker than that in the baseline specification (Column (4) of Table 1), as the effect of fixed-line diffusion on the ICT skills of 20–34 year olds is not anymore statistically significantly different from that of 55–65 year olds (i.e., the baseline category). The magnitude of the age-interactions is also reduced. One potential explanation for the attenuated age pattern is that residualized ICT skills measure "pure" ICT skills, as they are net of numeracy and literacy skills. These skills are likely very specific and higher-order ICT skills,[2] for which learning-by-doing is less relevant. Still, the results in Table C-1 indicate that our instruments capture the "right" variation and increase confidence that the returns to ICT skills estimates discussed above are not biased due to unobserved skills of PIAAC respondents.

Note that the value of these placebo tests hinges on the extent to which residualized (i.e., net of ICT skills) numeracy and literacy skills are rewarded on the labor market. If there were small or zero returns to these residualized skills, we could not isolate the wage effect of ICT skills from that of other relevant skill dimensions. However, Table C-2 reveals that the wage returns to numeracy and literacy skills are still substantial when controlling for ICT skills. In fact, the part of numeracy (literacy) skills that is unrelated to ICT skills accounts for 79 (75) percent of their wage returns. We are thus confident that we isolate ICT skills from the part of other skill domains that is most relevant on the labor market.

Column (7) of Table C-1 shows that in the sample of first-generation immigrants, there is no pronounced age pattern in the effect of exogenous broadband availability on ICT skills (Column (4) of Table 1 shows the corresponding results for our baseline sample of natives and second-generation immigrants).[3] If at all, earlier broadband availability reduces the gap in ICT skills between immigrants aged 55–65 and the younger immigrant cohorts, possibly reflecting that the oldest cohort has lived longest in the PIAAC test country (and is thus most affected by early broadband access). The fact that we can hardly ascribe first-generation immigrants' ICT skills to broadband Internet access in the PIAAC test country provides a rationale to exclude first-generation immigrants from the main analysis.

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[2] Supporting evidence for this comes from the fact that, compared to their non-residualized counterpart, residualized ICT skills are high only in a small set of occupations; that is, for ICT professionals and ICT technicians. This suggests that residualized ICT skills measure a specific (and likely narrow) set of ICT skills which are relevant in only few occupations.

[3] This result is not due to insufficient age variation in the sample of first-generation immigrants; in fact, the age variation is very similar as in our baseline sample.

*Within-Germany Analysis.* We also need to ensure that our within-Germany specification isolates the effect of ICT skills on wages from the effect of general ability, as we have done above for the international sample. Table C-3 presents the analogous placebo tests for the German sample. While neither numeracy nor literacy skills are systematically affected by the threshold instrument, the relationship between ICT skills and the instrument has the expected negative sign even conditional on the other skill domains. Table C-4 shows that the threshold dummy does not affect the ICT skills of first-generation immigrants, who are unlikely to have acquired ICT skills in Germany.

## II. *Exclusion Restriction: Potential Direct Wage Effects of Broadband*

Our international IV analysis exploits variation based on differences in the effect of exogenous broadband availability on ICT skills across age cohorts. Therefore, our strategy captures potential direct effects of broadband Internet on current wages levels (e.g., lower transaction costs and a more rapid diffusion of ideas) to the extent that young and older workers share equally the fruits of the new technology. However, the exclusion restriction of our instruments would be violated if these direct wage effects of broadband Internet followed the same age pattern as ICT skills do.

A major concern is that broadband is directly productive for firms, affecting wages of workers irrespective of their own usage of ICT skills. One may argue that when firms get broadband Internet earlier (or cheaper), they will invest more in capital that is complementary to this technology. Even in the most extreme case of no learning-by-doing effects in the accumulation of ICT skills, returns to ICT skills may still change as a result of a ICT capital-skill complementarity, and there is no a priori reason to believe that the level of this complementarity is the same for different cohorts. In Column (2) of Table C-5, we assess whether broadband affects workers' wages due to the accumulation of ICT capital (vis-à-vis ICT skills) by controlling for country-level ICT capital (in 2012) interacted with age cohorts. We still observe learning-by-doing effects—the interactions of fixed-line diffusion with age in the first stage are very similar to those in the baseline (Column (1))[4]—and estimated returns to ICT skills remain statistically significant and sizeable. As expected, the coefficient on ICT skills decreases compared to the baseline because investment in ICT capital is likely one channel through which returns to ICT skills materialize. Thus, while our results suggest that there is indeed a ICT capital-skill complementarity, it is unlikely that potential direct productivity effects of ICT capital invalidate the exclusion restriction.

[4] Column (1) of Table 6 shows the baseline results in the full sample of 19 countries. We could not obtain data on ICT capital in two countries, Germany and Poland. However, first-stage and second-stage results in the smaller sample are very similar to those in the full sample (e.g., returns to ICT skills are 0.214 vs. 0.236 in the full sample).

Another way to account for direct productivity effects of broadband is to control for alternative broadband access technologies which did not induce learning-by-doing effects in ICT skills. As noted in Czernich et al. (2011), broadband rollout is also determined by the spread of the cable TV network before broadband was introduced. However, preexisting cable TV diffusion should not exhibit learning-by-doing effects of a substantive magnitude due to a direct "distraction effect" from watching TV. For instance, data from American Time Use Survey reveal that in 2003 the average American spent 2.58 hours per day in front of the TV but only spent 0.08 hours per day on the phone. Therefore, the direct distraction effect of the cable TV network is likely far higher than that of voice telephony. In line with this reasoning, we find no significant age pattern in the effect of traditional cable TV diffusion on ICT skills (see first stage in Column (3) of Table C-5). Controlling for a potential age pattern in direct productivity effects of broadband induced by traditional cable TV networks in Column (3) also barely changes the baseline returns to ICT skills.

In Section 3.3., we also argued that new technologies like mobile Internet through 3G or, more recently, 4G reduced the reliance on fixed-line broadband technologies to access the Internet and build up ICT skills. We further argued that if mobile technologies are primarily used by younger persons, it may partly explain why we observe relatively small effects of exogenous fixed-line broadband diffusion on the ICT skills of persons in the younger age cohorts in PIAAC. Column (4) of Table C-5 shows that the effect of mobile telephone diffusion (measured in 2012)[5] on ICT skills indeed decreases steadily in age, with ICT skills of persons aged 20–34 benefitting by far the most from mobile Internet access.[6] Controlling for direct wage effects of broadband through mobile access technologies reduces estimated returns to ICT skills, but returns remain statistically significant and sizeable. This also holds when we simultaneously include preexisting cable TV diffusion and mobile telephone diffusion (Column (5)).

It is hardly surprising that the estimated returns to ICT skills decrease when ICT capital or mobile-phone diffusion are included as controls, because both are measured in 2012, that is, post-treatment. (Recall that the variation in broadband Internet availability that we draw on to explain ICT skills mainly comes from the early years of the Internet, that is, the first half of the 2000s; see Section 3.1.) Countries with a ICT-savvy population also make use of their ICT skills by investing more in ICT capital or by developing a better infrastructure (e.g., smartphone networks). These are therefore channels for the wage effects of ICT skills to materialize. However, it is interesting to

[5] The diffusion of mobile telephones has mainly enabled the provision of wireless broadband services (OECD, 2013c). Data on mobile telephone diffusion refer to 2012 to allow for learning-by-doing effects of wireless broadband access to materialize (4G was commercially introduced only in December 2009).

[6] Note that the inverted-U-shaped age pattern in the effect of fixed-line networks on ICT skills becomes even more pronounced when age effects in mobile Internet access are accounted for.

observe that, while these mechanisms can explain part of the returns to ICT skills, returns estimates remain significant even when controlling for them.

Moreover, based on available evidence, broadband Internet seems to have, at best, small positive wage effects on average. For instance, Kolko (2012) finds that broadband expansion did not affect average wages in U.S. ZIP code areas between 1999 and 2006. Similarly, Forman et al. (2012) find that advanced Internet technology and wage growth were generally unrelated in the USA in the period 1995–2000. These findings for the United States are corroborated by Falck et al. (2014) for Germany in the period 2004–2008 and by Poy and Schueller (2020) for Northern Italy in the period 2008–2013. However, while average wages seem to be unaffected by the availability of broadband Internet, Akerman et al. (2015) document a skill bias in wage effects of broadband Internet. The authors study the skill complementarity of broadband Internet using the expansion of broadband infrastructure in Norway in the 2000s as a natural experiment. They find that firms' access to broadband Internet raises (lowers) wages of skilled (unskilled) workers.

Such skill bias in the effect of broadband Internet would also raise concern if the share of high-skilled individuals varied across age cohorts. Indeed, the share of high-skilled individuals is larger among younger age cohorts than among older age cohorts in most PIAAC countries, reflecting the expansion of tertiary education in many countries in recent years.[7] To address this issue, we reweight individuals in our sample so that the share of high-skilled individuals is the same in each age cohort within a country. We restrict the sample to workers aged 30 years or more to ensure that we do not misclassify workers because they had not yet finished their university education. The results of this exercise are shown in Column (2) of Table C-6. Estimated returns (23 percent) are somewhat larger than the baseline estimate using the original PIAAC weights (18 percent), and remain statistically significant.[8]

In Column (3) of Table C-6, we return to the sample of workers aged 20–65 and add a control variable for the percentage of persons completing tertiary education by country and age cohort. This variable reflects variations in the quality of the labor force over time, which may also affect the market returns to (ICT) skills. The aggregate composition of the labor force has the expected negative sign, suggesting that a larger share of individuals completing university education indicates

[7] The difference in the share of university graduates between the youngest age group (30–34) and the oldest age group (55–65) is most pronounced in Ireland (31 pp.), the United Kingdom (19 pp.), Denmark (15 pp.), Korea (15 pp.), and Sweden (15 pp.). However, in Austria, Estonia, the Slovak Republic, and the United States, the share of university graduates is even larger in the oldest age group than in the youngest group.

[8] Analogously, one potential concern in the within-Germany analysis is that the share of university-educated workers differs systematically between areas above and below the 4,200-meter threshold. It is therefore reassuring that the threshold instrument is not significantly associated with the share of university-educated workers in a municipality, neither in the full sample nor in the no own MDF sample (results available upon request).

lower selectivity of that educational type (Hanushek et al., 2017). However, estimated returns to ICT skills are qualitatively the same as in the baseline specification (Column (4) of Table 1).[9]

Similarly, differential occupational distribution of employment across age groups might raise concern since occupational selection is an important mechanism explaining positive returns to ICT skills (see Section 7). To address this issue, we reweight individuals in our sample such that the share of a highly ICT-affine occupations is the same in each age cohort within a country. Results are shown in Table C-7.[10] In Column (2), we follow the classification of ICT occupations by the International Labour Organization (ILO, 2006). According to this definition, ICT occupations comprise production and operations managers (ISCO 13), ICT professionals (ISCO 25), ICT technicians (ISCO 35), and electrotechnology trades workers (ISCO 74).[11] In Column (3), we apply a narrower definition of ICT occupations including only ICT professionals and ICT technicians. In both specifications, estimated returns to ICT skills are somewhat smaller than the baseline estimate using the original PIAAC weights (25 percent; see Column 1), but remain statistically significant and sizeable.

The above evidence notwithstanding, there is additional reason to believe that potential direct productivity and wage effects are unlikely to bias our returns to ICT skills estimates. Figure 3 revealed that preexisting fixed-line networks are a good predictor of early broadband Internet penetration but do not well explain contemporaneous diffusion. In other words, our instruments induce variation in ICT skills that stems more from early differences than from contemporaneous differences in broadband penetration. Therefore, direct productivity and wage effects from contemporaneous broadband Internet use in firms should be unrelated to our instruments.

It would also be a threat to our identification strategy if online job search improved job matching, rendering workers more productive. However, although online job markets were introduced during the early phase of broadband diffusion, they were not widely used in the period 2000–2012. Employing annual household survey data from the German Socio-Economic Panel (SOEP) (Wagner et al., 2007), we observe that the share of persons who found a job through the Internet ranges from only 1 percent in 2000 to 17 percent in 2012 (see Figure C-1). For comparison, the share of persons who found a job through personal contacts is above 30 percent throughout

[9] We obtain very similar results in the sample of employees aged 30–65 years.

[10] The PIAAC Public Use File reports occupations for Austria, Canada, Estonia, and Finland only at the one-digit level. Since this level of occupational detail is not sufficient to identify ICT occupations, we drop these countries in this analysis.

[11] In ILO (2006), information technology trainers (ISCO 2356) are also counted as ICT occupations. We refrain from including them here because we can only add complete two-digit occupations and information technology trainers make up only a small part of the whole teaching force (ISCO 23).

this period, making it by far the most important job search channel. Furthermore, it is reassuring for our cross-country IV strategy that the use of online job search channels does not systematically vary with age. Figure C-1 shows that job search follows very similar patterns for our four age cohorts. Even among the 20–34-year olds, who appear to be the most frequent users of the Internet for job search, personal contacts are by far the most important channel. In addition, Kuhn and Mansour (2014) point out that successful online job search does not lead to higher wages than traditional job search methods.

However, although, on average, there may be no direct effect of broadband availability on wages through improved job matching, online job search may lead to higher wages for some age groups (e.g., younger workers). We test for age effects in the relationship between online job search and wage growth between jobs by again employing the SOEP data. We construct a sample of individuals with job-to-job transition(s) between 2000 and 2012 who were aged 20–65 years in the year they reported a job change. The variable of interest is a binary variable that equals 1 if the respondent found her new job through Internet job search, and 0 otherwise. Depending on the specification, this variable is interacted with age cohort dummies. Following Kuhn and Mansour (2014), we control for gender, marriage status, an interaction of gender and marriage status, educational attainment, and migration status. Results are shown in Table C-8. In Columns (1) and (2), the dependent variable is the log wage of the respondent's current job, and we control for the wage in the previous year, as proposed by Kuhn and Mansour (2014). Consistent with previous results, we detect no significant relationship between Internet job search and wage growth on average (Column (1)). However, this relationship does not exhibit any age pattern either; in Column (2), the main effect of Internet job search and all interactions with age cohorts are small and insignificant. The same holds when we use a direct measure of wage growth between jobs as the dependent variable in Columns (3) and (4). Overall, there is no evidence in support of either an average effect or an age-dependent effect of Internet job search on wage growth.

### *III. Exclusion Restriction: Age-Specific Omitted Variables*

As outlined above, the exclusion restriction of our international IV approach would be violated only if potential direct productivity effects of broadband would be asymmetric across age cohorts, that is, if they followed the same inverted U-shaped age pattern as the effect of technologically determined broadband availability on ICT skills does. There are several reasons why productivity effects of broadband may be age-specific. First, the work by Autor and Dorn (2009) shows that when exposed to technological change and trade, younger workers are more flexible than older workers in adjusting to new occupations. This could make it easier for younger workers to reap the rewards of rising productivity due to broadband Internet. Furthermore, Bloom et al. (2012) provide evidence that U.S. firms are often better able to benefit from ICT investment than their foreign competitors because they are more able to implement organizational reforms necessary for ICT investment to unfold its productivity impacts. A firm's ability to implement organizational changes may also interact with the age structure of the workforce since a younger workforce may more easily adapt to a new environment. More generally, we are worried that estimated returns to ICT skills may partly be driven by demand-side considerations, in particular, the differential availability of job opportunities which (a) raise wages, (b) are correlated with ICT skills, and (c) are age-specific.

Table C-9 tests whether our baseline results are potentially confounded by country-specific and/or industry-specific omitted variables that are heterogeneous across age groups. In Column (1), we add country-specific linear age trends to the baseline model to account for unobserved age effects in earnings (e.g., direct productivity effects of broadband that are linear in age). In this regression, we identify effects using only deviations from the country-level mean age trends in earnings. In Column (2), we replace country-specific age trends with industry fixed effects and industry-specific age trends, differentiating between 104 different industries.[12] Country-specific age trends, industry-specific age trends, and the respective fixed effects are included simultaneously in Column (3). Finally, Column (4) includes a full set of country-by-industry fixed effects (1214 in total) and also interacts them with age (another 1214 trend variables). This model controls for all confounding factors that are specific to countries and industries, even those that differently affect young and old workers. Thus, neither differences in firm culture or management practices giving rise to age-biased differential productivity effects of broadband across country-industry cells nor differential country-industry growth driving age-specific differences in the availability of ICT-intensive jobs are a threat in this estimation. At the same time, this very demanding specification accounts for different industrial structures of the economies and even for the country-specific industry composition.

Across specifications in Table C-9, returns to ICT skills remain highly significant and even increase somewhat as compared to the baseline estimate once we include country-specific age trends. This suggests a considerable heterogeneity in the age-earnings relationship across countries which age cohort dummies included in the baseline model (controlling for general age effects in earnings) are not able to pick up. One potential reason for this heterogeneity in the age-earnings profiles are the substantial differences in the degree of earnings inequality across OECD countries (e.g., Hanushek et al., 2015), reflecting the extent to which countries reward the skills of their

[12] We use the International Standard Industrial Classification (ISIC) at the two-digit level.

populations. In fact, when we add to the baseline specification interactions of a country's level of earnings inequality in 1996 with age cohorts, estimated returns to ICT skills increase to the same magnitude as in Columns (1), (3), and (4) of Table C-9. Likewise, when we split the sample at the median of pre-broadband earnings inequality, we find larger returns to ICT skills in countries with above-median earnings inequality (results are available on request).

Furthermore, if country-specific age effects would be a first-order concern, the residuals from the baseline regression would systematically deviate from a normal distribution. Figure C-2 plots the quantiles of the residuals against the quantiles of the normal distribution. The residuals are strikingly close to a normal distribution in all countries, again refuting the claim that our results can be attributed to a country-specific age structure in earnings.

We also provide a comprehensive analysis of whether the cross-country heterogeneity in fixed-line diffusion (which is part of our identification) is truly orthogonal to potential omitted variables that might increase wages of a specific age cohort. In Tables C-9 and C-10, we augment the baseline specification (Column (4) of Table 1) with controls for several pre-broadband variables that may still affect today's wage levels, interacted with the age cohorts. In Table C-10, we include variables capturing a country's general technology affinity (i.e., share of high-tech exports and share of STEM graduates), specialization in ICT products (i.e., ICT goods trade as a share of total trade), and technological composition of industries (i.e., industry computer use).[13] In Table C-11, we consider pre-broadband economic indicators (i.e., average years of schooling, population size, and GDP per capita).[14] Reassuringly, the estimated returns to ICT skills remain significant and sizeable throughout all specifications.

Results are also robust to a number of alternative specifications not shown in the above tables. For instance, when added to the baseline model, interactions of age with features of country labor markets (i.e., strength of employment protection, bargaining coverage, and existence or bite of the minimum wage) leave estimated returns to skills qualitatively unchanged. We also find that the diffusion of broadband Internet is not significantly correlated with changes in these labor-market institutions over time. This refutes the possible claim that countries with faster technological change systematically decreased employment protection to increase the flexibility of their labor markets, affecting primarily older workers (for instance, the "Hartz reforms" in Germany).

[13] Since the sample changes between models due to data availability, we report returns to ICT skills from the baseline specification in the respective sample at the bottom of Table C-10.

[14] All outcomes refer to 1996 unless otherwise noted. Data on ICT goods trade, STEM graduates, and GDP per capita are provided by the OECD. Data on high-technology exports are from the World Bank. Data on industry-level computer use are taken from Autor et al. (2003) and are recoded to the ISIC industry classification (data refer to 1997). Data on years of schooling and population are from Barro and Lee (2013) and refer to 1995.

Moreover, in the within-Germany analysis, all results remain robust when we include county-level controls for the industry structure of employment (i.e., employment shares of construction, manufacturing, and services) in the pre-broadband era.

In light of the evidence presented above, we are confident that our results are not driven by omitted factors that give rise to higher relative wages for middle-aged workers (vis-à-vis young workers and old workers) irrespective of their own usage of ICT skills.

## *IV. Sorting: Selective Internal Migration*

In our within-Germany IV model, one of the key threats to identification is that people selectively relocate from dwellings at a distance to the MDF above the 4,200-meter threshold to dwellings below the threshold. To empirically assess this concern, we first draw on data from the German regional statistics that contain information for the universe of West German municipalities ($n > 8000$) in the period 2001–2012. We calculate the annual out-migration rate for each municipality as the number of inhabitants moving out of a municipality in a given year relative to the municipality's total population.[15] Using a pooled regression with only year dummies and a threshold indicator as regressors, we find that the average out-migration rate between 2001 and 2012 is 5.9 percent in municipalities below the threshold.[16] The coefficient on the threshold dummy is very small at –0.07 percentage points and negative, implying an out-migration rate in above-threshold municipalities of 5.8 percent. Due to the large sample size, the threshold coefficient is statistically significant at the 10 percent level. Regressions for each individual year show that the threshold coefficient is always negligible in economic terms, being statistically significant only in the years 2001–2005. Thus, results consistently show that people are not systematically leaving areas where broadband Internet is technologically not available.

We complement this municipality-level analysis by again employing annual household survey data from the SOEP, which allow us to identify moves at a very granular regional level (including moves within the same neighborhood). We use the exact geo-coordinates of the SOEP households in West Germany for the survey waves 2000–2010 to calculate whether a household has changed its distance to the MDF between two survey waves.[17] In our sample, we can follow 14,568 households for at least two consecutive waves and over an average period of 6.1 years. Among these households, 996 (6.8 percent) lived in a dwelling situated above the threshold in at least one

[15] We use *ArcGIS* to account for territorial changes between 2001 and 2012.

[16] As in our wage analysis, the threshold dummy is a binary variable taking the value 1 if a municipality is above the 4,200-meter threshold and 0 otherwise.

[17] The geo-coordinates of the SOEP households are confidential and available only onsite at the DIW in Berlin.

survey wave. Overall, we observe 6,449 relocations in our sample. From a simple individual fixed-effects regression with a relocation dummy as outcome variable and the lagged threshold dummy as the only explanatory variable, we derive an average relocation rate of 7.3 percent (6.2 percent) for households from dwellings situated below (above) the threshold; the difference between both location rates is not statistically significant. Thus, corroborating the results from the municipality-level analysis, the average relocation rate of above-threshold households is again somewhat lower than that of below-threshold households. Furthermore, 93.8 percent of the relocations do not involve crossing the threshold.

In summary, the out-migration patterns employing either the German regional statistics or the SOEP are remarkably similar (out-migration rates of 5.9/5.8 percent vs. 7.3/6.2 percent), although both datasets contain observations at different levels of aggregation. Reassuringly, both analyses indicate that sorting related to broadband Internet access is unlikely to be a threat to our identification strategy.

## Additional References


Bloom, Nicholas, Raffaella Sadun, and John Van Reenen (2012): "Americans Do IT Better: US Multinationals and the Productivity Miracle." *American Economic Review*, 102(1): 167–201.

Forman, Chris, Avi Goldfarb, and Shane Greenstein (2012): "The Internet and Local Wages: A Puzzle." *American Economic Review*, 102(1): 556–575.

Hanushek, Eric A., Guido Schwerdt, Ludger Woessmann, and Lei Zhang (2017): "General Education, Vocational Education, and Labor-Market Outcomes over the Life-Cycle." *Journal of Human Resources*, 52(1): 48–78.

ILO (2006): *Occupations in Information and Communications Technology. Options for Updating the International Standard Classification of Occupations*. Geneva: International Labour Organization.

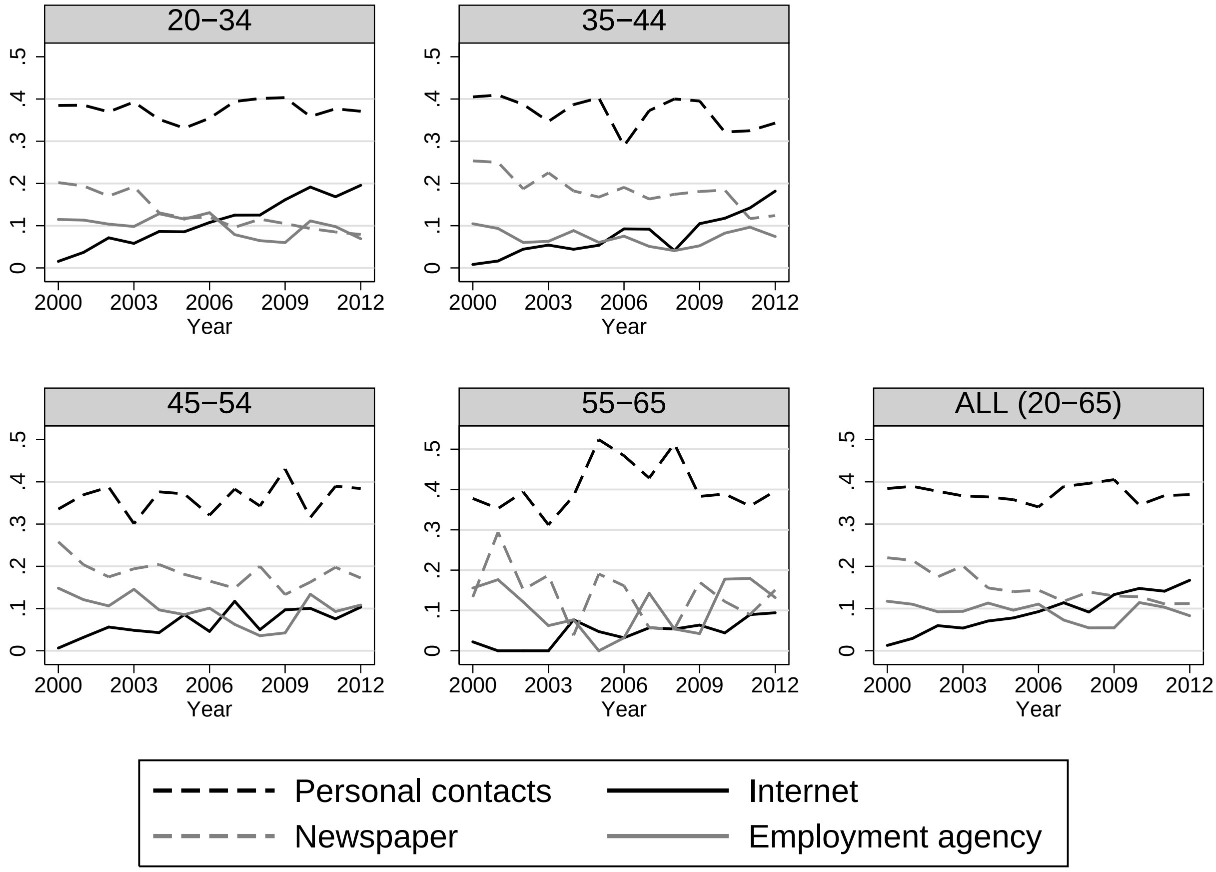
Kolko, Jed (2012): "Broadband and Local Growth." *Journal of Urban Economics*, 71(1): 100–113.

Mani, Sunil (2004): "Exports of High Technology Products from Developing Countries: Are the Figures Real or Are They Statistical Artefacts?" *Innovation, Learning, and Technological Dynamism of Developing Countries* (Sunil Mani and Henny Romijn, Eds.), 12–47. Tokio: United Nations University Press.

OECD (2013c): *OECD Communications Outlook 2013*. Paris: Organisation for Economic Co-operation and Development.

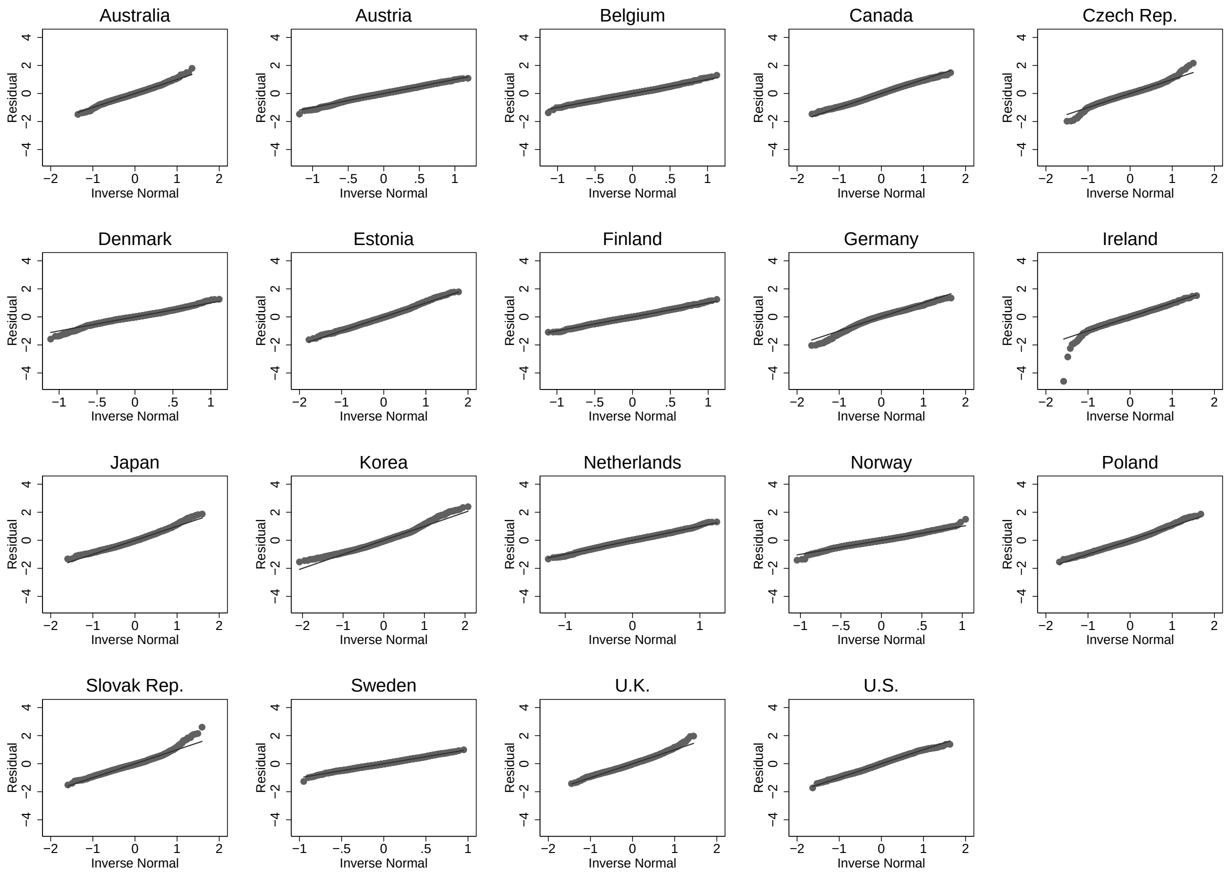
Poy, Samuele and Simone Schueller (2020): "Internet and Voting in the Web 2.0 Era: Evidence from a Local Broadband Policy." *Research Policy*, 49(1).

Figure C-1: Importance of Different Methods for Successful Job Search by Age Group




*Notes:* Graph shows shares of different job finding methods in the period 2000–2012. Shares are calculated as number of persons finding a new job via personal contacts (i.e., acquaintances, friends, and relatives), Internet, job agencies, and newspaper, respectively, as a fraction of all persons who reported to have found a new job in the respective year. A "new job" includes positions at a new employer and starting work for the first time; this definition excludes, for example, persons who found another position within the same firm, returned to their old employer after a leave, became self-employed, or stayed in the same company after apprenticeship, government employment program, or being a freelancer. We also drop from the sample individuals with missing information on whether or how they found a new job. Employment agency includes the German *Arbeitsamt/Agentur fuer Arbeit* as well as the more recent concept of Job Centers (also including social services). Shares do not add up to 100 percent because seldom used methods of finding a job are excluded for ease of exposition. *Data source:* German Socio-Economic Panel (SOEP).

Figure C-2: Q-Q Plots for Residuals of Baseline Model




*Notes:* Graph shows quantile-quantile plots for each country from the two-stage Least squares regressions of Equation (1). The quantiles of the residual from this regression are plotted against the corresponding quantiles from the normal distribution, depicted by the straight solid line. *Data sources:* ITU, PIAAC.

Table C-1: International Evidence: Placebo Tests

| Sample: | Natives & 2nd-gen. immigrants (baseline sample) | | | | | | 1st-gen. immigrants |
|---|---|---|---|---|---|---|---|
| Dependent variable: | Numeracy | Literacy | ICT | Numeracy (residualized) | Literacy (residualized) | ICT (residualized) | ICT |
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) |
| Fixed-line diffusion × age 20–34 | 0.184* | –0.125 | 0.141 | 0.319* | –0.223 | 0.248 | –0.789 |
| | (0.099) | (0.095) | (0.103) | (0.166) | (0.170) | (0.173) | (0.508) |
| Fixed-line diffusion × age 35–44 | 0.107 | –0.063 | 0.313*** | 0.203 | –0.108 | 0.513*** | –0.865* |
| | (0.103) | (0.100) | (0.108) | (0.173) | (0.178) | (0.183) | (0.502) |
| Fixed-line diffusion × age 45–54 | –0.029 | –0.024 | 0.121 | –0.041 | –0.042 | 0.196 | –0.571 |
| | (0.107) | (0.103) | (0.110) | (0.179) | (0.184) | (0.185) | (0.489) |
| ICT skills | 0.675*** | 0.737*** | | | | | |
| | (0.004) | (0.004) | | | | | |
| Numeracy skills | | | 0.332*** | | | | |
| | | | (0.007) | | | | |
| Literacy skills | | | 0.549*** | | | | |
| | | | (0.007) | | | | |
| Individual characteristics | X | X | X | X | X | X | X |
| Country fixed effects | X | X | X | X | X | X | X |
| R squared (adjusted) | 0.58 | 0.63 | 0.67 | 0.10 | 0.04 | 0.10 | 0.09 |
| Individuals | 53,879 | 53,879 | 53,879 | 53,879 | 53,879 | 53,879 | 6,298 |

*Notes:* Least squares regressions weighted by sampling weights (giving same weight to each country). Sample: employees aged 20–65 years. No first-generation immigrants in Columns (1)–(6); only first-generation immigrants in Column (7). *1st-gen. immigrants:* participant born abroad; at least one parent as well. Numeracy, literacy, and ICT skills are standardized to SD 1 across countries. Numeracy and literacy skills in Columns (4) and (5) are the residual of least squares regressions of numeracy and literacy skills, respectively, on ICT skills. ICT skills in Column (6) are the residual of a least squares regression of ICT skills on numeracy and literacy skills. *Fixed-line diffusion:* voice-telephony penetration rate (telephone access lines per inhabitant) in 1996. Omitted age category is 55–65 years. Individual characteristics are age cohorts and gender. Robust standard errors in parentheses. Significance levels: * p<0.10, ** p<0.05, *** p<0.01. *Data sources:* ITU, PIAAC.

Table C-2: Wage Effects of Non-Residualized vs. Residualized Numeracy and Literacy Skills

| Dependent variable: log gross hourly wage | | | | |
|---|---|---|---|---|
| | Numeracy | | Literacy | |
| | (1) | (2) | (3) | (4) |
| Numeracy skills | 0.148*** | 0.117*** | | |
| | (0.003) | (0.004) | | |
| Literacy skills | | | 0.136*** | 0.102*** |
| | | | (0.003) | (0.004) |
| ICT skills | | 0.040*** | | 0.043*** |
| | | (0.004) | | (0.004) |
| Age 20–34 | –0.299*** | –0.324*** | –0.325*** | –0.345*** |
| | (0.008) | (0.008) | (0.008) | (0.008) |
| Age 35–44 | –0.088*** | –0.103*** | –0.104*** | –0.116*** |
| | (0.008) | (0.008) | (0.008) | (0.008) |
| Age 45–54 | –0.038*** | –0.045*** | –0.044*** | –0.050*** |
| | (0.008) | (0.008) | (0.008) | (0.008) |
| Female | –0.137*** | –0.140*** | –0.167*** | –0.164*** |
| | (0.005) | (0.005) | (0.005) | (0.005) |
| Country fixed effects | X | X | X | X |
| Individuals | 53,879 | 53,879 | 53,879 | 53,879 |

*Notes:* Regressions weighted by sampling weights (giving same weight to each country). Least squares estimations. Sample: employees aged 20–65 years, no first-generation immigrants. Dependent variable is *log gross hourly wage*, measured in PPP-USD. Skill measures are standardized to SD 1 across countries. Robust standard errors in parentheses. Significance levels: * p<0.10, ** p<0.05, *** p<0.01. *Data source:* PIAAC.

Table C-3: Within-Germany Evidence: Placebo Tests Using Other Skill Domains

| | Panel A: Full Sample | | | | | |
|---|---|---|---|---|---|---|
| Dependent variable: cognitive skills in | Numeracy | Literacy | ICT | Numeracy (residualized) | Literacy (residualized) | ICT (residualized) |
| | (1) | (2) | (3) | (4) | (5) | (6) |
| Threshold | 0.044 | –0.020 | –0.139*** | 0.038 | –0.025 | –0.128*** |
| | (0.054) | (0.065) | (0.047) | (0.055) | (0.065) | (0.047) |
| ICT skills | 0.713*** | 0.772*** | | | | |
| | (0.018) | (0.017) | | | | |
| Numeracy skills | | | 0.330*** | | | |
| | | | (0.032) | | | |
| Literacy skills | | | 0.516*** | | | |
| | | | (0.032) | | | |
| Individual characteristics | X | X | X | X | X | X |
| Municipality characteristics | X | X | X | X | X | X |
| R squared (adjusted) | 0.59 | 0.63 | 0.68 | 0.05 | 0.01 | 0.06 |
| Individuals | 1,849 | 1,849 | 1,849 | 1,849 | 1,849 | 1,849 |
| Municipalities | 204 | 204 | 204 | 204 | 204 | 204 |

| | Panel B: No Own MDF Sample | | | | | |
|---|---|---|---|---|---|---|
| Dependent variable: cognitive skills in | Numeracy | Literacy | ICT | Numeracy (residualized) | Literacy (residualized) | ICT (residualized) |
| | (1) | (2) | (3) | (4) | (5) | (6) |
| Threshold | –0.033 | 0.007 | –0.203*** | –0.005 | 0.014 | –0.189*** |
| | (0.069) | (0.078) | (0.059) | (0.076) | (0.070) | (0.056) |
| ICT skills | 0.644*** | 0.746*** | | | | |
| | (0.060) | (0.053) | | | | |
| Numeracy skills | | | 0.168 | | | |
| | | | (0.099) | | | |
| Literacy skills | | | 0.666*** | | | |
| | | | (0.081) | | | |
| Individual characteristics | X | X | X | X | X | X |
| Municipality characteristics | X | X | X | X | X | X |
| R squared (adjusted) | 0.57 | 0.66 | 0.69 | 0.01 | –0.02 | 0.03 |
| Individuals | 160 | 160 | 160 | 160 | 160 | 160 |
| Municipalities | 18 | 18 | 18 | 18 | 18 | 18 |

*Notes:* Least squares regressions weighted by sampling weights (giving same weight to each municipality). Sample: West German employees aged 20–65 years, no first-generation immigrants. Panel A shows results for all municipalities in the sample. In Panel B, sample is restricted to municipalities without an own main distribution frame (MDF). Numeracy, literacy, and ICT skills are standardized to SD 1 within Germany. Numeracy and literacy skills in Columns (4) and (5) are the residual of least squares regressions of numeracy and literacy skills, respectively, on ICT skills. ICT skills in Column (6) are the residual of a least squares regression of ICT skills on numeracy and literacy skills. *Threshold:* equal to 1 if a municipality is more than 4,200 meters away from its MDF (lower probability of DSL availability), and 0 otherwise. Distance calculations are based on municipalities' geographic centroid. Municipality characteristics are unemployment rate in 1999 (i.e., share of unemployed individuals in the working-age population aged 18-–65 years) and population share of individuals older than 65 in 1999. Individual characteristics are a quadratic polynomial in work experience and gender. Robust standard errors, adjusted for clustering at the municipality level, in parentheses. Significance levels: * p<0.10, ** p<0.05, *** p<0.01. *Data sources:* German Broadband Atlas, German Federal Statistical Office, PIAAC.

Table C-4: Within-Germany Evidence: Placebo Tests Using Migration Status

| Dependent variable: ICT skills | Natives & 2nd-gen. immigrants (baseline sample) (1) | 1st-gen. immigrants (2) |
|---|---|---|
| Threshold | –0.369*** | 0.256 |
| | (0.114) | (0.333) |
| Unemployment rate in 1999 | –2.582** | –4.443 |
| | (1.261) | (3.727) |
| Population share 65+ in 1999 | –0.886 | 3.653 |
| | (1.253) | (4.132) |
| Experience | –0.004 | –0.031 |
| | (0.007) | (0.022) |
| Experience$^2$ (/100) | –0.052*** | 0.030 |
| | (0.016) | (0.054) |
| Female | –0.149*** | –0.276* |
| | (0.046) | (0.142) |
| R squared (adjusted) | 0.13 | 0.05 |
| Individuals | 1,849 | 237 |
| Municipalities | 204 | 129 |

*Notes:* Least squares regressions weighted by sampling weights (giving same weight to each municipality). Sample: West German employees aged 20–65 years. No first-generation immigrants in Column (1); only first-generation immigrants in Column (2). *1st-gen. immigrants:* participant born abroad; at least one parent as well. ICT skills are standardized to SD 1 within Germany. *Threshold:* equal to 1 if a municipality is more than 4,200 meters away from its MDF (lower probability of DSL availability), and 0 otherwise. Distance calculations are based on municipalities' geographic centroid. *Unemployment rate in 1999:* municipality-level share of unemployed individuals in the working-age population (18–65 years). *Population share 65+ in 1999:* municipality-level population share of individuals older than 65 years. *Experience:* years of actual work experience. Robust standard errors, adjusted for clustering at the municipality level, in parentheses. Significance levels: * p<0.10, ** p<0.05, *** p<0.01. *Data sources:* German Broadband Atlas, German Federal Statistical Office, PIAAC.

Table C-5: ICT Capital and Alternative Broadband-Access Technologies

| Second stage (Dependent variable: log gross hourly wage) | | | | | |
|---|---|---|---|---|---|
| | | ICT | Alternative | | |
| | Baseline | capital | broadband technologies | | |
| | (1) | (2) | (3) | (4) | (5) |
| ICT skills | 0.236*** | 0.141** | 0.261*** | 0.122* | 0.122* |
| | (0.078) | (0.064) | (0.079) | (0.069) | (0.070) |
| Individual characteristics | X | X | X | X | X |
| Country fixed effects | X | X | X | X | X |
| First stage (Dependent variable: ICT skills) | | | | | |
| Fixed-line diffusion (1996) × age 20–34 | 0.384** | 0.484*** | 0.362** | 0.627*** | 0.608*** |
| | (0.155) | (0.160) | (0.152) | (0.158) | (0.154) |
| Fixed-line diffusion (1996) × age 35–44 | 0.839*** | 1.042*** | 0.837*** | 1.001*** | 0.998*** |
| | (0.168) | (0.174) | (0.164) | (0.170) | (0.166) |
| Fixed-line diffusion (1996) × age 45–54 | 0.253 | 0.310* | 0.286* | 0.366** | 0.399** |
| | (0.170) | (0.175) | (0.166) | (0.172) | (0.169) |
| ICT capital (2012) × age 20–34 | | 0.004*** | | | |
| | | (0.001) | | | |
| ICT capital (2012) × age 35–44 | | 0.002 | | | |
| | | (0.001) | | | |
| ICT capital (2012) × age 45–54 | | 0.000 | | | |
| | | (0.001) | | | |
| Cable TV diffusion (1996) × age 20–34 | | | 0.124 | | 0.096 |
| | | | (0.139) | | (0.140) |
| Cable TV diffusion (1996) × age 35–44 | | | 0.013 | | 0.017 |
| | | | (0.147) | | (0.147) |
| Cable TV diffusion (1996) × age 45–54 | | | –0.163 | | –0.173 |
| | | | (0.152) | | (0.152) |
| Mobile diffusion (2012) × age 20–34 | | | | 0.564*** | 0.560*** |
| | | | | (0.063) | (0.063) |
| Mobile diffusion (2012) × age 35–44 | | | | 0.384*** | 0.384*** |
| | | | | (0.067) | (0.067) |
| Mobile diffusion (2012) × age 45–54 | | | | 0.256*** | 0.251*** |
| | | | | (0.068) | (0.068) |
| Cragg-Donald Wald F statistic | 28.5 | 34.6 | 26.5 | 34.6 | 31.6 |
| Stock&Yogo critical value | 9.1 | 9.1 | 9.1 | 9.1 | 9.1 |
| Individuals | 53,879 | 48,859 | 53,879 | 53,879 | 53,879 |

*Notes:* Two-stage least squares regressions weighted by sampling weights (giving same weight to each country). Sample: employees aged 20–65 years, no first-generation immigrants. Dependent variable in second stage is *log gross hourly wage*, measured in PPP-USD. Column (1) replicates the baseline model in Column (4) of Table 1. *Fixed-line diffusion:* voice-telephony penetration rate (telephone access lines per inhabitant). *ICT capital:* ICT equipment net fixed assets (System of National Accounts 2008, in current prices) from the OECD National Accounts Statistics; data are not available in Germany and Poland. ICT capital, cable TV diffusion and mobile-phone diffusion, each interacted with age groups, are added as controls. *Cable TV diffusion:* cable television subscriptions per inhabitant. *Mobile diffusion:* mobile-cellular telephone subscriptions per inhabitant. Omitted age category is 55–65 years. Individual characteristics are age cohorts and gender. Robust standard errors in parentheses. Significance levels: * p<0.10, ** p<0.05, *** p<0.01. *Data sources:* ITU, OECD, PIAAC.

Table C-6: International Evidence: Accounting for the Different Educational Compositions Across Age Groups

| Second stage (Dependent variable: log gross hourly wage) | Baseline (1) | Reweighted skill shares (2) | Labor force composition (3) |
|---|---|---|---|
| ICT skills | 0.184** | 0.227* | 0.165** |
| | (0.081) | (0.123) | (0.079) |
| Age 30–34 | –0.255*** | –0.305*** | –0.393*** |
| | (0.071) | (0.108) | (0.068) |
| Age 35–44 | –0.155*** | –0.187** | –0.142*** |
| | (0.055) | (0.085) | (0.051) |
| Age 45–54 | –0.069** | –0.081* | –0.062** |
| | (0.027) | (0.042) | (0.026) |
| Female | –0.173*** | –0.164*** | –0.156*** |
| | (0.013) | (0.019) | (0.010) |
| % with tertiary education, country-cohort | | | –0.035 |
| | | | (0.073) |
| Country fixed effects | X | X | X |
| First stage (Dependent variable: ICT skills) | | | |
| Fixed-line diffusion × age 30–34 | 0.283 | 0.129 | 0.446*** |
| | (0.186) | (0.209) | (0.160) |
| Fixed-line diffusion × age 35–44 | 0.801*** | 0.638*** | 0.836*** |
| | (0.172) | (0.199) | (0.168) |
| Fixed-line diffusion × age 45–54 | 0.234 | 0.188 | 0.255 |
| | (0.173) | (0.205) | (0.170) |
| Cragg-Donald Wald F statistic | 27.3 | 16.4 | 27.2 |
| Stock&Yogo critical value | 9.1 | 9.1 | 9.1 |
| Individuals | 40,480 | 40,480 | 53,879 |

*Notes:* Two-stage least squares regressions weighted by sampling weights (giving same weight to each country). Sample: employees aged 30–65 years (20–65 years in Column (3)), no first-generation immigrants. Dependent variable in second stage, *log gross hourly wage*, is measured in PPP-USD. Column (1) replicates the baseline model in Column (4) of Table 1 for the sample of persons aged 30 and above. In Column (2), weights are adjusted such that in each country and age cohort, the share of persons with tertiary education equals the country-specific share in the age cohort 35–44 years (other age cohorts are 30–34 years, 45–54 years, and 55–65 years). In Column (3), we add the percentage completing university education in each country and age cohort (calculated from the PIAAC data). ICT skills are standardized to SD 1 across countries. *Fixed-line diffusion:* voice-telephony penetration rate (telephone access lines per inhabitant) in 1996. Omitted age category is 55–65 years. Robust standard errors in parentheses. Significance levels: * $p<0.10$, ** $p<0.05$, *** $p<0.01$. *Data sources:* ITU, PIAAC.

Table C-7: International Evidence: Accounting for the Different Occupational Compositions Across Age Groups

| Second stage (Dependent variable: log gross hourly wage) | Baseline (1) | Reweighted ICT occ shares (broad definition) (2) | Reweighted ICT occ shares (narrow definition) (3) |
|---|---|---|---|
| ICT skills | 0.249*** | 0.201** | 0.164* |
| | (0.085) | (0.099) | (0.096) |
| Age 30–34 | –0.482*** | –0.447*** | –0.412*** |
| | (0.073) | (0.086) | (0.083) |
| Age 35–44 | –0.210*** | –0.174*** | –0.151** |
| | (0.057) | (0.067) | (0.065) |
| Age 45–54 | –0.096*** | –0.082** | –0.071** |
| | (0.028) | (0.033) | (0.033) |
| Female | –0.132*** | –0.141*** | –0.147*** |
| | (0.012) | (0.015) | (0.014) |
| Country fixed effects | X | X | X |
| First stage (Dependent variable: ICT skills) | | | |
| Fixed-line diffusion × age 30–34 | 0.399** | 0.359** | 0.406** |
| | (0.178) | (0.180) | (0.177) |
| Fixed-line diffusion × age 35–44 | 0.829*** | 0.763*** | 0.779*** |
| | (0.192) | (0.193) | (0.190) |
| Fixed-line diffusion × age 45–54 | 0.168 | 0.131 | 0.145 |
| | (0.193) | (0.197) | (0.193) |
| Cragg-Donald Wald F statistic | 22.0 | 21.8 | 26.6 |
| Stock&Yogo critical value | 9.1 | 9.1 | 9.1 |
| Individuals | 35,923 | 35,923 | 35,923 |

*Notes:* Two-stage least squares regressions weighted by sampling weights (giving same weight to each country). Sample: employees aged 20–65 years, no first-generation immigrants. Estimation excludes four countries without occupational information at the two-digit ISCO level (i.e., without Austria, Canada, Estonia, Finland). Dependent variable in second stage, *log gross hourly wage*, is measured in PPP-USD. Column (1) replicates the baseline model in Column (4) of Table 1 for the sample of countries with two-digit occupational information. In Columns (2) and (3), weights are adjusted such that in each country and age cohort, the share of persons working in ICT occupations equals the country-specific share in the age cohort 35–44 years (other age cohorts are 30–34 years, 45–54 years, and 55–65 years). In Column (2), ICT occupations are defined as production and operations managers (ISCO 13), ICT professionals (ISCO 25), ICT technicians (ISCO 35), and electrotechnology trades workers (see ILO, 2006); in Column (3), ICT occupations are defined as ICT professionals (ISCO 25) and ICT technicians (ISCO 35). ICT skills are standardized to SD 1 across countries. *Fixed-line diffusion:* voice-telephony penetration rate (telephone access lines per inhabitant) in 1996. Omitted age category is 55–65 years. Robust standard errors in parentheses. Significance levels: * p<0.10, ** p<0.05, *** p<0.01. *Data sources:* ITU, PIAAC.

Table C-8: Does Online Job Search Affect Wages?

| Dependent variable: | | | | |
|---|---|---|---|---|
| | log gross hourly wage | | wage growth | |
| | (1) | (2) | (3) | (4) |
| Previous log wage | 0.565*** | 0.565*** | | |
| | (0.014) | (0.014) | | |
| Internet job search | 0.025 | 0.019 | –0.010 | –0.012 |
| | (0.017) | (0.105) | (0.019) | (0.088) |
| Internet job search × age 20–34 | | 0.002 | | 0.029 |
| | | (0.108) | | (0.092) |
| Internet job search × age 35–44 | | 0.011 | | –0.037 |
| | | (0.108) | | (0.092) |
| Internet job search × age 45–54 | | 0.016 | | –0.029 |
| | | (0.109) | | (0.093) |
| Age 20–34 | 0.073*** | 0.073*** | 0.138*** | 0.134*** |
| | (0.025) | (0.026) | (0.026) | (0.028) |
| Age 35–44 | 0.122*** | 0.122*** | 0.079*** | 0.082*** |
| | (0.025) | (0.026) | (0.026) | (0.027) |
| Age 45–54 | 0.086*** | 0.085*** | 0.066** | 0.068** |
| | (0.025) | (0.026) | (0.027) | (0.028) |
| Individual characteristics | X | X | X | X |
| Year fixed effects | X | X | X | X |
| R squared (adjusted) | 0.55 | 0.55 | 0.01 | 0.01 |
| Individuals | 5,649 | 5,649 | 5,649 | 5,649 |

*Notes:* Least squares regressions pooling the years 2000–2012. Sample: German employees aged 20–65 years (in the respective year) with a job-to-job transition. Dependent variable in Columns (3) and (4), *wage growth*, is calculated as the difference between the log of the hourly wage in the year individuals reported having undergone a job-to-job transition and the log of the hourly wage in the year before; hourly wages are calculated as proposed in Brenke (2012), that is, gross monthly wage divided by the usual weekly working hours*4.2. *Previous log wage:* gross hourly wage in the job before the job change, measured in logarithms. *Internet job search:* respondent found her current job through the Internet. Individual characteristics are gender, marriage status, interaction between gender and marriage status, level of schooling (less than high school, high school, more than high school), and migration status. Omitted age category is 55–65 years. Robust standard errors, adjusted for clustering at the individual level, in parentheses. Significance levels: * p<0.10, ** p<0.05, *** p<0.01. *Data source:* German Socio-Economic Panel (SOEP).

Table C-9: Country-Specific and Industry-Specific Age Trends

| Dependent variable: log gross hourly wage | | | | |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| ICT skills | 0.436*** | 0.246*** | 0.426*** | 0.460*** |
| | (0.103) | (0.088) | (0.111) | (0.132) |
| Country fixed effects [19] | X | X | X | X |
| Industry fixed effects [104] | | X | X | X |
| Country X industry fixed effects [1214] | | | | X |
| Country-specific linear age trends [19] | X | | X | X |
| Industry-specific linear age trends [104] | | X | X | X |
| Country-industry-specific linear age trends [1214] | | | | X |
| Individual characteristics | X | X | X | X |
| First stage (Dependent variable: ICT skills) | | | | |
| Fixed-line diffusion × age 20–34 | –0.007 | 0.331** | 0.069 | 0.033 |
| | (0.415) | (0.152) | (0.398) | (0.406) |
| Fixed-line diffusion × age 35–44 | 0.568** | 0.733*** | 0.561** | 0.458 |
| | (0.284) | (0.163) | (0.273) | (0.284) |
| Fixed-line diffusion × age 45–54 | 0.150 | 0.254 | 0.174 | 0.113 |
| | (0.207) | (0.164) | (0.197) | (0.196) |
| Cragg-Donald Wald F statistic | 22.6 | 22.3 | 19.6 | 13.0 |
| Stock&Yogo critical value | 9.1 | 9.1 | 9.1 | 9.1 |
| Individuals | 53,651 | 53,651 | 53,651 | 53,651 |

*Notes:* Two-stage least squares regressions weighted by sampling weights (giving same weight to each country). Sample: employees aged 20–65 years, no first-generation immigrants; workers who do not report their industry at the two-digit level are excluded. Dependent variable in second stage is *log gross hourly wage*, measured in PPP-USD. ICT skills are standardized to SD 1 across countries. Omitted age category is 55–65 years. Numbers in brackets indicates the number of fixed effects. Individual characteristics are age (linear), age cohorts, and gender. Robust standard errors in parentheses. Significance levels: * $p<0.10$, ** $p<0.05$, *** $p<0.01$. *Data sources:* ITU, PIAAC.

Table C-10: Further Country-Level Controls from the Pre-Broadband Era: Technology Indicators

| Additional country control indicated in column heading | %High-tech exports | %ICT trade | %STEM graduates | Computer use (Autor et al.) | All |
|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) |
| ICT skills | 0.256*** | 0.342*** | 0.339*** | 0.160** | 0.249*** |
| | (0.077) | (0.090) | (0.082) | (0.079) | (0.076) |
| Individual characteristics | X | X | X | X | X |
| Country fixed effects | X | X | X | X | X |
| First stage (Dependent variable: ICT skills) | | | | | |
| Fixed-line diffusion × age 20–34 | 0.428*** | 0.403** | 0.268 | 0.443*** | 0.394 |
| | (0.158) | (0.171) | (0.250) | (0.157) | (0.259) |
| Fixed-line diffusion × age 35–44 | 0.903*** | 0.844*** | 1.107*** | 0.839*** | 1.221*** |
| | (0.169) | (0.184) | (0.271) | (0.168) | (0.277) |
| Fixed-line diffusion × age 45–54 | 0.362** | 0.242 | 0.344 | 0.285* | 0.395 |
| | (0.172) | (0.186) | (0.268) | (0.171) | (0.282) |
| Cragg-Donald Wald F statistic | 26.0 | 25.4 | 26.7 | 31.1 | 29.4 |
| Stock & Yogo critical value | 9.1 | 9.1 | 9.1 | 9.1 | 9.1 |
| Individuals | 51,612 | 51,253 | 44,898 | 53,030 | 40,814 |
| Returns in baseline specification | 0.218 | 0.298 | 0.392 | 0.219 | 0.316 |

*Notes:* Two-stage least squares regressions weighted by sampling weights (giving same weight to each country). Sample: employees aged 20–65 years, no first-generation immigrants. Dependent variable in second stage is *log gross hourly wage*, measured in PPP-USD. All additional country controls refer to 1996 unless otherwise noted and are interacted with the following age cohorts: 20–34 years, 35–44 years, 45–54 years, and 55–65 years. *%High-tech exports* in Column (1) is high-technology exports as a share of manufactured exports; high-technology exports are the top 10 manufactured products with the highest embodied R&D spending relative to the value of shipments, such as in aerospace, computers, pharmaceuticals, scientific instruments, and electrical machinery (Mani, 2004); data not available for Belgium. *%ICT trade* in Column (2) is measured as the share of ICT goods trade in total trade; data not available for Estonia and refer to 1997 in the Slovak Republic. *%STEM graduates* in Column (3) is the share of STEM graduates in all university graduates; STEM subjects are natural science, medical science, mathematics, computer science, engineering, and architecture; data are unavailable for Estonia, Korea, Poland, and the Slovak Republic. *Computer use* in Column (4) is taken from Autor et al. (2003); refers to 1997. Industry computer use frequencies were calculated from the Current Population Survey as the weighted fraction of currently employed workers aged 18–65 who answered yes to the question, "Do you use a computer directly at work?" within consistent CIC industries; data are converted to two-digit ISIC codes (there is no corresponding industry code for 849 individuals in PIAAC). Column (5) includes interactions with all country-level variables from Columns (1)–(4). Since sample size changes between specifications due to missing country data, last row reports estimated returns to ICT skills from the baseline specification (Column (4) in Table 1) in the respective sample. Omitted age category is 55–65 years. Individual characteristics are age cohorts and gender. Robust standard errors in parentheses. Significance levels: * p<0.10, ** p<0.05, *** p<0.01. *Data sources:* Autor et al. (2003), ITU, Mani (2004), OECD, PIAAC, World Bank.

Table C-11: Further Country-Level Controls from the Pre-Broadband Era: Economic Indicators

| Additional country control indicated in column heading | Years schooling | Population | GDP per capita | All |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| ICT skills | 0.188** | 0.180** | 0.378*** | 0.401*** |
| | (0.073) | (0.074) | (0.090) | (0.097) |
| Individual characteristics | X | X | X | X |
| Country fixed effects | X | X | X | X |
| First stage (Dependent variable: ICT skills) | | | | |
| Fixed-line diffusion × age 20–34 | 0.456*** | 0.593*** | 0.735*** | 0.692*** |
| | (0.154) | (0.157) | (0.224) | (0.223) |
| Fixed-line diffusion × age 35–44 | 0.893*** | 0.964*** | 1.132*** | 1.054*** |
| | (0.167) | (0.170) | (0.242) | (0.241) |
| Fixed-line diffusion × age 45–54 | 0.284* | 0.398** | 0.363 | 0.306 |
| | (0.169) | (0.171) | (0.239) | (0.238) |
| Cragg-Donald Wald F statistic | 30.8 | 30.3 | 16.9 | 15.2 |
| Stock & Yogo critical value | 9.1 | 9.1 | 9.1 | 9.1 |
| Individuals | 53,879 | 53,879 | 53,879 | 53,879 |

*Notes:* Two-stage least squares regressions weighted by sampling weights (giving same weight to each country). Sample: employees aged 20–65 years, no first-generation immigrants. Dependent variable in second stage is *log gross hourly wage*, measured in PPP-USD. Additional country controls refer to 1995 unless otherwise noted and are interacted with the following age cohorts: 20–34 years, 35–44 years, 45–54 years, and 55–65 years. *GDP per capita* in Column (3) is in logs and refers to 1996. Column (4) includes interactions with all country-level variables from Columns (1)–(3). Omitted age category is 55–65 years. Individual characteristics are age cohorts and gender. Robust standard errors in parentheses. Significance levels: * p<0.10, ** p<0.05, *** p<0.01. *Data sources:* Barro and Lee (2013), ITU, PIAAC.

## Online Appendix D: Robustness

*International Analysis.* In Table D-1, we show that our results do not depend on the inclusion or exclusion of specific age cohorts. In Column (1), we estimate returns to ICT skills for the entire PIAAC age sample, that is, also including workers aged 16–19 years. In Columns (2)–(4), we gradually drop the youngest age cohorts to take into account that early career observations may understate the full value of skills because of imperfect job matches (e.g., Jovanovic, 1979). In Columns (5)–(8), we proceed similarly, but omit workers from age 60 onward to show that our results are unaffected by cross-country differences in retirement and labor-force participation rates.

*International Analysis and Within-Germany Analysis.* In Tables D-2 and D-3, we present robustness checks designed to test the sensitivity of our main results to adding further controls at the individual level. If our identification strategy addresses omitted-variable bias in the estimation of skill returns, adding other variables that are important for wage determination should leave the estimated IV coefficient on ICT skills unaffected. We add control variables that differently account for the tenure-earnings relationship (i.e., quadratic polynomial in actual work experience in the international analysis and quadratic polynomial in age in the within-Germany analysis), an indicator of full-time employment, and an indicator for whether a respondent is a native or a second-generation immigrant. Reassuringly, the estimated returns to ICT skills remain very similar when including these additional controls, providing evidence that our IV strategy does indeed identify variation in ICT skills that is independent of potentially omitted variables at the individual level.

Finally, we also assess the robustness of our results when assigning people with missing ICT skills a very low value of ICT skills (e.g., zero ICT skills; minimum ICT skills either of all respondents or of the respondents in the same country; one percent of the median observed ICT skills in a country). To take into account that ICT skills can be missing for different reasons, we also estimated specifications in which persons who reported to have no computer experience or who failed an initial short computer test were assigned zero ICT skills and persons who refused to take part in the computer-based assessment were assigned different percentiles ($25^{th}$, $50^{th}$, $75^{th}$) of the country-specific ICT skill distribution. Returns to ICT skills tend to increase in these more inclusive samples, which is hardly surprising given that people without ICT skills information often work in low-paying jobs. Moreover, our sample comprises only employed workers, which introduces potential complications due to endogenous selection into employment. One way to take the employment effects of skills into account in our wage regression is to include the non-employed in the sample and assign them a very low log wage value (we use one percent of the median observed wage in a country). In such a model, estimated returns to skills increase from our baseline estimate of 0.236 to 0.432. The first stage is also very similar as in our baseline sample—and in fact becomes even stronger—when we include non-employed in the analysis.[1]

## Additional References


Jovanovic, Boyan (1979): "Job Matching and the Theory of Turnover." *Journal of Political Economy*, 87(5): 972–990.


[1] Detailed results for these extended samples are available upon request.

Table D-1: International Evidence: Other Age Samples

| Second stage (Dependent variable: log gross hourly wage) | Including oldest age group | | | | Excluding oldest age group | | | |
|---|---|---|---|---|---|---|---|---|
| | 16–65 | 20–65 | 25–65 | 30–65 | 16–59 | 20–59 | 25–59 | 30–59 |
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
| ICT skills | 0.310*** | 0.236*** | 0.157** | 0.184** | 0.380*** | 0.306*** | 0.214** | 0.229*** |
| | (0.080) | (0.078) | (0.079) | (0.081) | (0.087) | (0.084) | (0.083) | (0.085) |
| Age 16–19 | –0.956*** | | | | –0.995*** | | | |
| | (0.051) | | | | (0.050) | | | |
| Age 20–34 | –0.520*** | –0.457*** | –0.305*** | –0.255*** | –0.577*** | –0.519*** | –0.364*** | –0.302*** |
| | (0.070) | (0.069) | (0.072) | (0.071) | (0.071) | (0.069) | (0.070) | (0.068) |
| Age 35–44 | –0.239*** | –0.191*** | –0.139** | –0.155*** | –0.280*** | –0.237*** | –0.183*** | –0.191*** |
| | (0.054) | (0.053) | (0.054) | (0.055) | (0.054) | (0.052) | (0.051) | (0.052) |
| Age 45–54 | –0.108*** | –0.086*** | –0.061** | –0.069** | –0.127*** | –0.108*** | –0.086*** | –0.090*** |
| | (0.027) | (0.026) | (0.027) | (0.027) | (0.024) | (0.023) | (0.023) | (0.023) |
| Female | –0.137*** | –0.148*** | –0.161*** | –0.173*** | –0.130*** | –0.140*** | –0.154*** | –0.167*** |
| | (0.010) | (0.010) | (0.011) | (0.013) | (0.010) | (0.010) | (0.011) | (0.013) |
| Country fixed effects | X | X | X | X | X | X | X | X |
| First stage (Dependent variable: ICT skills) | | | | | | | | |
| Fixed-line diffusion × age 16–19 | –0.016 | | | | –0.034 | | | |
| | (0.252) | | | | (0.267) | | | |
| Fixed-line diffusion × age 20–34 | 0.398** | 0.384** | 0.419*** | 0.283 | 0.367** | 0.354** | 0.386** | 0.241 |
| | (0.156) | (0.155) | (0.162) | (0.186) | (0.179) | (0.178) | (0.184) | (0.206) |
| Fixed-line diffusion × age 35–44 | 0.849*** | 0.839*** | 0.823*** | 0.801*** | 0.819*** | 0.808*** | 0.792*** | 0.764*** |
| | (0.168) | (0.168) | (0.168) | (0.172) | (0.190) | (0.189) | (0.190) | (0.193) |
| Fixed-line diffusion × age 45–54 | 0.259 | 0.253 | 0.246 | 0.234 | 0.233 | 0.227 | 0.221 | 0.203 |
| | (0.170) | (0.170) | (0.170) | (0.173) | (0.192) | (0.191) | (0.191) | (0.195) |
| Cragg-Donald Wald F statistic | 23.9 | 28.5 | 26.2 | 27.3 | 21.0 | 24.7 | 22.3 | 23.5 |
| Stock & Yogo critical value | 10.3 | 9.1 | 9.1 | 9.1 | 10.3 | 9.1 | 9.1 | 9.1 |
| Individuals | 56,630 | 53,879 | 47,402 | 40,480 | 53,930 | 51,179 | 44,702 | 37,780 |

*Notes:* Two-stage least squares regressions weighted by sampling weights (giving same weight to each country). Sample: employees (age range is indicated in the column heading), no first-generation immigrants. Dependent variable in second stage, *log gross hourly wage*, is measured in PPP-USD. ICT skills are standardized to SD 1 across countries. *Fixed-line diffusion:* voice-telephony penetration rate (telephone access lines per inhabitant) in 1996. Omitted age category is 55–65 years. Robust standard errors in parentheses. Significance levels: * $p<0.10$, ** $p<0.05$, *** $p<0.01$. *Data sources:* ITU, PIAAC.

Table D-2: International Evidence: Further Individual-Level Controls

| Second stage (Dependent variable: log gross hourly wage) | | | | | |
|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) |
| ICT skills | 0.236*** | 0.229*** | 0.225*** | 0.227*** | 0.188** |
| | (0.078) | (0.078) | (0.077) | (0.077) | (0.076) |
| Experience | | 0.033*** | | | 0.032*** |
| | | (0.001) | | | (0.001) |
| Experience$^2$ (/100) | | –0.049*** | | | –0.050*** |
| | | (0.003) | | | (0.003) |
| Full-time | | | 0.040*** | | 0.012 |
| | | | (0.012) | | (0.013) |
| Native | | | | –0.005 | –0.007 |
| | | | | (0.009) | (0.009) |
| Individual characteristics | X | X | X | X | X |
| Country fixed effects | X | X | X | X | X |
| First stage (Dependent variable: ICT skills) | | | | | |
| Fixed-line diffusion × age 20–34 | 0.384** | 0.298* | 0.400*** | 0.396** | 0.335** |
| | (0.155) | (0.155) | (0.155) | (0.155) | (0.154) |
| Fixed-line diffusion × age 35–44 | 0.839*** | 0.790*** | 0.848*** | 0.846*** | 0.814*** |
| | (0.168) | (0.167) | (0.167) | (0.168) | (0.166) |
| Fixed-line diffusion × age 45–54 | 0.253 | 0.215 | 0.253 | 0.257 | 0.221 |
| | (0.170) | (0.168) | (0.169) | (0.170) | (0.168) |
| Cragg-Donald Wald F statistic | 28.5 | 27.6 | 29.1 | 28.7 | 28.6 |
| Stock & Yogo critical value | 9.1 | 9.1 | 9.1 | 9.1 | 9.1 |
| Individuals | 53,879 | 53,879 | 53,879 | 53,879 | 53,879 |

*Notes:* Two-stage least squares regressions weighted by sampling weights (giving same weight to each country). Sample: employees aged 20–65 years, no first-generation immigrants. Dependent variable in second stage, *log gross hourly wage*, is measured in PPP-USD. ICT skills are normalized with SD 1 across countries. Baseline in Column (1) replicates Table 1, Column (4). *Experience:* years of actual work experience. *Full-time:* 1 = working more than 30 hours per week (Australia and Austria: self-reported information whether a respondent works full-time; Canada: no information on full-time working status, all workers assumed to be full-time workers). *Native:* 1 = native (participant and both parents born in the country of residence); 0 = second-generation immigrant (mother, father, or both born abroad; participant born in country of residence). *Fixed-line diffusion:* voice-telephony penetration rate (telephone access lines per inhabitant) in 1996. Omitted age category is 55–65 years. Individual characteristics are age cohorts and gender. Robust standard errors in parentheses. Significance levels: * $p<0.10$, ** $p<0.05$, *** $p<0.01$. *Data sources:* ITU, PIAAC.

Table D-3: Within-Germany Evidence: Further Individual-Level Controls

| Second stage (Dependent variable: log gross hourly wage) | Full sample | | | | | No own MDF sample | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) | (10) |
| ICT skills | 0.306** | 0.300** | 0.311** | 0.302** | 0.306** | 0.521** | 0.550** | 0.518** | 0.585** | 0.619** |
| | (0.151) | (0.152) | (0.150) | (0.151) | (0.153) | (0.213) | (0.223) | (0.209) | (0.231) | (0.244) |
| Age | | 0.064*** | | | 0.068*** | | –0.045 | | | –0.047 |
| | | (0.015) | | | (0.015) | | (0.076) | | | (0.084) |
| $Age^2$ (/100) | | –0.061*** | | | –0.062*** | | 0.064 | | | 0.067 |
| | | (0.019) | | | (0.019) | | (0.091) | | | (0.099) |
| Full-time | | | 0.146*** | | 0.196*** | | | 0.165 | | 0.152 |
| | | | (0.040) | | (0.039) | | | (0.182) | | (0.233) |
| Native | | | | –0.024 | –0.005 | | | | 0.469** | 0.500** |
| | | | | (0.033) | (0.032) | | | | (0.239) | (0.225) |
| Individual characteristics | X | X | X | X | X | X | X | X | X | X |
| Municipality characteristics | X | X | X | X | X | X | X | X | X | X |
| First stage (Dependent variable: ICT skills) | | | | | | | | | | |
| Threshold | –0.369*** | –0.364*** | –0.370*** | –0.369*** | –0.365*** | –0.517*** | –0.491*** | –0.513*** | –0.474*** | –0.443*** |
| | (0.114) | (0.116) | (0.114) | (0.114) | (0.116) | (0.153) | (0.134) | (0.153) | (0.149) | (0.131) |
| Kleibergen-Paap F statistic | 10.5 | 9.9 | 10.5 | 10.5 | 9.9 | 11.5 | 13.5 | 11.2 | 10.2 | 11.3 |
| Individuals | 1,849 | 1,849 | 1,849 | 1,849 | 1,849 | 160 | 160 | 160 | 160 | 160 |
| Municipalities | 204 | 204 | 204 | 204 | 204 | 18 | 18 | 18 | 18 | 18 |

*Notes:* Two-stage least squares regressions weighted by sampling weights (giving same weight to each municipality). Sample: West German employees aged 20–65 years, no first-generation immigrants. "No own MDF sample" includes only municipalities without an own main distribution frame (MDF). ICT skills are normalized with SD 1 within Germany. Baseline in Column (1) (Column (6)) replicates Table 2, Column (6) (Column (8)). *Full-time:* 1 = working more than 30 hours per week. *Native:* 1 = native (participant and both parents born in Germany); 0 = second-generation immigrant (mother, father, or both born abroad; participant born in Germany). *Threshold:* binary variable equal to 1 if a municipality is more than 4,200 meters away from its MDF (lower probability of DSL availability), and 0 otherwise. Distance calculations are based on municipalities' geographic centroid. Municipality characteristics are unemployment rate in 1999 (i.e., share of unemployed individuals in the working-age population aged 18-–65 years) and population share of individuals older than 65 in 1999. Individual characteristics are a quadratic polynomial in work experience and gender. Robust standard errors, adjusted for clustering at the municipality level, in parentheses. Significance levels: * $p<0.10$, ** $p<0.05$, *** $p<0.01$.
*Data sources:* German Broadband Atlas, German Federal Statistical Office, PIAAC.