Returns to ICT Skills*

Oliver Falck, Alexandra Heimisch, Simon Wiederhold†

Abstract

How important is mastering information and communication technology (ICT) in modern labor markets? Previous research offers no guidance in assessing the labor-market returns to ICT skills, primarily because skill data have been unavailable. We draw on unique data that provide internationally comparable information on ICT skills in 19 countries. Using an instrument that leverages cross-country variation in the technologically determined probability of having Internet access, we find that ICT skills are substantially rewarded in the labor market. Placebo estimations show that exogenous Internet availability cannot explain numeracy or literacy skills, suggesting that our identifying variation is independent of a person's general ability. We also exploit technological peculiarities that determine Internet availability across German municipalities and confirm the findings from the cross-country analysis. Our results further suggest that the proliferation of computers complements workers in executing abstract tasks that use and reinforce ICT skills.

Keywords: ICT skills; broadband; earnings; international comparisons

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† Falck: University of Munich, ifo Institute, and CESifo, falck@ifo.de; Heimisch: ifo Institute at the University of Munich, heimisch@ifo.de. Wiederhold: ifo Institute at the University of Munich and CESifo, wiederhold@ifo.de.

1. Introduction

"The new literacy" is the term Neelie Kroes, Vice-President of the European Commission, uses to describe an individual's skill in mastering information and communication technology (ICT). She justifies her choice of this phrase 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] Even though this statement is intuitively plausible, empirical evidence on how ICT skills affect labor-market outcomes has yet to be provided. The main reason for this lack of research is the unavailability of data to measure ICT skills consistently within or across countries, and the difficulty of drawing credible inferences when it is not known whether an individual's level of ICT skill is just a reflection of other characteristics related to wages. Using novel, internationally comparable data on individuals' skills in ICT and other domains across 19 countries, this paper is the first to provide a rigorous empirical assessment of the wage returns to ICT skills.

Our primary data source is the Programme for the International Assessment of Adult Competencies (PIAAC). PIAAC is the first-ever study to assess individuals' ICT skills (called "problem-solving in technology-rich environments" in PIAAC). The survey was conducted between August 2011 and March 2012 in 24 developed economies, which together represent about 75 percent of the worldwide GDP. PIAAC was designed to provide representative measures of the cognitive skills possessed by adults (aged 16 to 65 years) in three different domains (i.e., numeracy, literacy, and ICT). Having skill data from various domains offers a unique opportunity to test whether the estimated effect of ICT skills on wages is merely a reflection of a person's general ability.

Our identification strategy is based on the idea that ICT skills are developed by performing ICT-related tasks and that having access to the Internet is a precondition for this type of learning by doing.[2] We thus exploit exogenous variation in the probability of having Internet access in a cross-country instrumental-variable approach. This variation stems from international differences in the rollout of traditional fixed-line voice-telephony networks, which, only years later, were upgraded to

[1] http://www.getonlineweek.eu/vice-president-neelie-kroes-says-digital-literacy-and-e-skills-are-the-new-literacy/; accessed July 19, 2015.

[2] Recently, a stream of literature has emerged on the effects of Internet use on various (social) outcomes (see, e.g., Bauernschuster, Falck, and Woessmann, 2014, for social interactions; Falck, Gold, and Heblich, 2014, for voting behavior; and Bhuller, Havnes, Leuven, and Mogstad, 2013, for sex crimes). Moreover, Bulman and Fairlie (2015) provide an excellent overview of the impact of computer and Internet use on the educational achievement of students.

provide high-speed Internet access (Czernich, Falck, Kretschmer, and Woessmann, 2011). We further argue, and provide evidence, that a higher technologically determined probability of having access to the Internet in a country increases the chance and duration of accumulating ICT skills through learning by doing. Conditioning our estimates on cross-country differences in the stage of economic development before the first emergence of high-speed Internet and in the general productivity level today, we can plausibly identify a causal impact of ICT skills on wages.

In addition to the cross-country instrumental-variable approach, we also exploit historical peculiarities in the rollout of traditional voice-telephony infrastructure within a single country—Germany. In the western part of Germany, the structure of the voice-telephony network was designed in the 1960s with the declared 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, the last-mile distance restricted the maximum bandwidth of broadband Internet about 40 years later. Beyond a certain distance threshold, high-speed Internet access was not feasible without major infrastructure investment, which excluded a large share of West German municipalities from early broadband Internet access (Falck, Gold, and Heblich, 2014). The technical threshold in the households' distance to the main network node to which they are connected provides exogenous variation in the availability of broadband Internet and, as a consequence, in ICT skills.

Our findings from both instrumental-variable approaches indicate a positive effect of ICT skills on wages that is both economically and statistically significant. In the cross-country analysis, an increase in ICT skills by one country-level standard deviation leads to a 7.5 percent increase in employee wages. In Germany, estimated returns to ICT skills are somewhat larger at 14 percent. These estimates control for a rich set of individual-level variables, including a person's acquired level of schooling. Moreover, we show in a placebo test that preexisting fixed-line diffusion (across countries) or technological peculiarities of the fixed-line network (within Germany) are not associated with any appreciable changes in numeracy or literacy skills, which we consider strong evidence that our identification strategy isolates the effect of ICT skills (vis-à-vis generic skills or general ability) on wages. Another placebo test shows that the extent of a country's traditional voice-telephony network is irrelevant in a sample of first-generation immigrants who are unlikely to have acquired ICT skills in the country in which they were tested in PIAAC. Furthermore, returns to ICT skills are negligible in occupations that involve little or no ICT skills to perform the required tasks, indicating that our estimated returns to ICT skills do not just reflect the wage effects of some unobserved country factors.

A unique feature of the PIAAC survey is that it combines individual-level information on ICT skills, computer use at work, and wages in a single dataset. This allows us to shed light on a potential mechanism driving returns to ICT skills, namely, that the proliferation of personal computers caused a shift away from routine tasks—that is, those more amenable to automatization—toward problem-solving and complex communication tasks (typically called "nonroutine abstract tasks").[3] We find that computer use at work is indeed strongly positively correlated with an occupation's abstract-task intensity and is negatively correlated with its routine-task intensity. This supports the main idea of the task-based approach that the upsurge of computers in recent decades complements workers in executing nonroutine abstract tasks, and substitutes for workers performing routine tasks. We also find that workers in occupations with high abstract (routine) task intensity have substantially higher (lower) ICT skills than workers in occupations that are not pervasive in these tasks. Thus, having high ICT skills seems to be a necessary prerequisite for performing jobs characterized by high abstract-task intensity, as workers need to have an excellent command of computers. Since abstract jobs pay substantial wage premia, this suggests a potential mechanism behind the positive wage returns to ICT skills in modern labor markets.[4]

Previous literature on the returns to computer skills in the labor market highlights the empirical challenges of attempting to estimate causal effects.[5] For example, an influential paper by DiNardo and Pischke (1997) suggests that computer users possess unobserved skills that might have little to do with computers per se but that increase their productivity. Our paper is the first to use a direct measure of ICT skill and estimate its impact on wages. Moreover, we also have information on worker skills in other domains, allowing us to rigorously address DiNardo and Pischke's concern

[3] This argument was first made by Autor, Levy, and Murnane (2003) when developing their task-based approach to skill-biased technological change. See also Autor, Katz, and Kearney (2006, 2008), Goos and Manning (2007), Black and Spitz-Oener (2010), Firpo, Fortin, and Lemieux (2011), Acemoglu and Autor (2011), Autor and Dorn (2013), Goos, Manning, and Salomons (2014), and Akerman, Gaardner, and Mogstad (2015). In an historical perspective, however, technology did not always benefit skilled workers performing abstract tasks. For example, in the beginning of the 19th century, automated looms replaced skilled weavers in the textile industry with a punch card and a few unskilled workers. Moreover, implementation of the Fordist assembly line in the automobile industry in the early 20th century increased the demand for routine tasks. See also Goldin and Katz (1996, 2009).

[4] See Akerman, Gaardner, and Mogstad (2015) for a task-based explanation of labor-market effects of broadband Internet adoption in Norway.

[5] See Draca, Sadun, and Van Reenen (2007) for a detailed review.

that observed wage differentials between workers with high versus low ICT skills are largely a reflection of unobserved worker heterogeneity.

Finally, our paper adds to the recently emerging stream of literature that regards direct measures of cognitive skills as more reliable proxies for effective human capital than acquired years of schooling (e.g., Hanushek and Kimko, 2000; Hanushek and Woessmann, 2008). However, the existing literature offers little guidance in assessing the magnitude of the labor-market returns to cognitive skills, as most of the previous evidence stems from the small number of U.S. panel datasets that follow tested students into their initial jobs.[6] A noticeable exception is the work by Hanushek, Schwerdt, Wiederhold, and Woessmann (2015), who also draw on the PIAAC data to produce new international evidence on the wage returns to cognitive skills. However, the authors do not attempt to specifically investigate the returns to ICT skills, which is the aim of this study. Moreover, although they do explore issues of causality by using several instrumental-variable approaches, they exploit plausibly exogenous variation in skills only in the United States, using changes in compulsory schooling laws across states over time. However, this source of identifying variation is unlikely to discriminate between different types of skills. We contribute to the discussion about causality in the returns-to-skills estimation by assessing the role of domain-specific skills for labor-market outcomes. Moreover, instead of relying solely on within-country variation in skills, our identification strategies exploit exogenous variation both across and within countries.

The paper is organized as follows. Section 2 describes the PIAAC data and the measurement of ICT skills. Section 3 outlines our cross-country and within-country identification strategies. Section 4 presents the results on the returns to ICT skills from the cross-country analysis, including placebo tests and robustness checks. Section 5 presents the corresponding within-country evidence. Section 6 discusses the relationship between the task content of occupations and (returns to) ICT skills. Section 7 concludes.

2. ICT Skills

One of the core features of this paper is its use of new and consistent international data on the ICT skills of the adult population. These data come from the Programme for the International

[6] Overviews of the existing evidence can be found in Bowles, Gintis, and Osborne (2001), Hanushek and Woessmann (2008), and Hanushek and Rivkin (2012).

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 the worldwide GDP.[7] PIAAC was designed to provide representative measures of cognitive skills possessed by adults aged 16 to 65 years, and had 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.

Along with information on cognitive skills, PIAAC also offers extensive information on respondents' individual and workplace characteristics, for instance, 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.

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.[8] The individual-level correlation of ICT skills with literacy (numeracy) is 0.77 (0.73), which is less strong than the correlation between numeracy and literacy (0.82). Still, all three skill domains appear to measure distinct dimensions of a respondent's skill set.[9]

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

[7] 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.

[8] 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, Wiederhold, and Ackermann-Piek (2014) for a discussion of the plausible values in PIAAC.

[9] 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. However, ICT skills were not assessed in IALS.

tasks" (OECD, 2013, p. 86).[10] 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. Often, solving the tasks required the 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 requests if reservation requests could not be accommodated.[11] In general, ICT skills as assessed in PIAAC measure the extent to which a participant can be regarded as a "digital native," that is, whether he or she is capable of using modern information and communication tools to get along in a digital world. Accordingly, the ICT test in PIAAC does not reflect proficiency in more specific computer skills like advanced programming.

ICT skills were assessed in a computer-based mode, so some basic knowledge regarding the use of computers was required to participate in the ICT skill test; 9.3 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 the basic ICT competencies, such as using a keyboard/mouse or scrolling through text on the screen; 4.9 percent of all participants did not pass this test and thus were also excluded from the ICT skills assessment. Finally, 10.2 percent of the participants opted to take the paper-based assessment without first taking the ICT core assessment, even though they reported some prior experience with computers.[12]

[10] *Literacy* is the ability to understand, evaluate, use, and engage with written texts to participate in society, to achieve one's goals, and to 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.

[11] See OCED (2013, p. 89) and OCED (2015, p. 39f.) for other examples of problem scenarios used in PIAAC to test participants' ICT skills. The ICT tasks to be solved by participants came in three different difficulty levels.

[12] Not surprisingly, people who took the paper-based assessment are on average older than people who took the computer-based assessment, which holds for all three types (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 possess, on average, lower numeracy and literacy skills. See also OECD (2015) and Rammstedt (2013).

In total, ICT skills could not be measured for about 24 percent of the population of PIAAC respondents. Persons without an ICT skills score are excluded from our sample.[13]Furthermore, the assessment of 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.[14] For reasons related to our identification strategy (see Section 3), in our main analysis we focus on 20–49-year-old natives and second-generation immigrants. This leaves us with a total of 40,865 individual-level observations.

Figure 1 depicts average ICT skills by country. The average level of ICT skill is 294 points, with an individual-level standard deviation of about 40 points (see also Table A-1). Respondents in Japan, Sweden, and Finland have the highest average scores, while respondents in the former communist countries (the Czech Republic, Estonia, Poland, and the Slovak Republic) and Ireland score lowest in the ICT skill assessment. The difference between Japan (the best-performing country with 306 points) and Poland (the worst-performing country with 276 points) amounts to almost 75 percent of a standard deviation.[15] The low level of ICT skills in Estonia is initially particularly surprising because the country is well known for providing easy and free broadband access to its population. However, a closer inspection of the data reveals that the low average proficiency in Estonia is mainly driven by the very low ICT skills of the older respondents in our sample (45–49 years), who grew up in a communist regime, while the ICT skills of respondents aged 20–24 years are close to the cross-country average for this age group. The age pattern in ICT skills is even more distinct for the Korean population, which also—perhaps surprisingly—has relatively low average ICT skills. Here, the 20–24 year olds are even among the top performers in the PIAAC assessment, while the 45–49

[13] Results are robust when we assign respondents with missing ICT skills the minimum ICT skills (either of all respondents or of the respondents in the same country) instead of dropping them from the sample. Moreover, the results continue to hold when we replace missing ICT skills with zero ICT skills. Our results are also robust when imputing missing ICT test scores using questions for assessing literacy and numeracy skills. For this end we regress ICT skills on numeracy or literacy questions that were asked in the same way in both the paper-based and computer-based mode. For each country individually, we then multiply the estimated coefficients with an indicator that evaluates to 1 if a person with missing ICT skills correctly answered the corresponding paper-based question (0 otherwise). Summing up over all questions and also accounting for the country-specific intercept, we arrive at ICT skill scores for persons whose scores were initially missing.

[14] In addition to the countries that did not test participants' ICT skills, we 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.

[15] Figure A-1, which shows the distribution of ICT skills within each country with the smoothed (kernel) fit for Japan for comparison, yields similar conclusions regarding the cross-country differences in ICT skills. We observe that the Nordic countries, especially Sweden and Finland, have skill distributions very similar to that of Japan, while the distributions in the post-communist countries and Ireland are shifted to the left.

year olds fall substantially short of international performance and, together with Estonia and Poland, are at the bottom of the international league tables.

Unsurprisingly, countries that perform on average worse in the ICT skills assessment also have a higher share of people for whom ICT skills are missing due to a lack of computer experience or due to opting out of the computer-based assessment mode; the correlation between a country's level of ICT skills and its share of people with missing ICT skills is quite strong at –0.61. For expositional purposes, we do not use raw scores in the subsequent regression analyses but standardize scores to have a mean of zero and standard deviation of one across countries.[16]

<< Figure 1 about here >>

Table A-1 shows the descriptive statistics of participants' characteristics for the pooled sample and separately for the 19 countries in the sample. The size of the estimation sample ranges from 1,375 persons in the Slovak Republic to 7,531 persons in Canada. The Canadian sample is much larger than those 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-$) across countries.[17] 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 160 percent of an international standard deviation. There is also considerable cross-country variation in our estimation sample in years of schooling, work experience, and gender composition.

[16] In the cross-country (within-country) IV strategy we use the country-level (German-municipality-level) standard deviation to standardize the skill test scores because it relies on between-country (between-municipality) variation. A country-level standard deviation amounts to 8.5 points on the PIAAC scale; a municipality-level standard deviation is 20.5 PIAAC points.

[17] 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, Schwerdt, Wiederhold, and Woessmann (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.

3. Estimation Strategy

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

$$\log w_{ic} = \beta_0 + \beta_1 ICT_{ic} + \boldsymbol{X_{ic}\beta_2} + \boldsymbol{X_c\beta_3} + \varepsilon_{ic}. \tag{1}$$

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 the "standard" Mincer controls (years of schooling, work experience, gender). $\boldsymbol{X_c}$ is a vector of country-level control variables, which we discuss in greater detail below. ε_{ic} is an error term. The coefficient of interest is β_1, which shows the wage change in percent when ICT skills increase by one unit.[18] Since ICT skills are *z*-standardized in the empirical analysis, β_1 is interpreted as the percentage increase in wages resulting from a one standard deviation increase in ICT skills.

In this basic regression framework, β_1 can hardly be interpreted as the causal effect of ICT skills on wages. The most obvious reasons for β_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, Schwerdt, Wiederhold, and Woessmann, 2015). Measurement error may occur if cognitive skills in PIAAC are just an error-ridden measure of the human capital relevant in the labor market, and the implicit errors can bias our estimates of the returns to ICT skills. Errors in the measurement of ICT skills can also occur if PIAAC respondents had a bad testing day or answered questions 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.[19] Moreover, higher earnings may actually lead to improvements in ICT skills, giving rise to the problem of reverse causality. Better jobs may be more likely to require and reinforce skills or they may provide the resources to invest in adult education and training. Finally, omitted-variable bias may arise because unobserved

[18] For the ease of exposition, we frequently refer to β_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, Lochner, and Todd (2006).

[19] Hanushek, Schwerdt, Wiederhold, and Woessmann (2015) instrument numeracy skills with literacy skills to address the attenuation bias arising from measurement error. However, this strategy does not correct any errors common to both skill domains and implicitly imposes the assumption that measurement errors are uncorrelated across skill domains. Our IV strategy provides a more encompassing solution to the measurement error problem.

variables like non-cognitive skills, personality traits, or family background could directly influence earnings and may also be related to ICT skills. While reverse causality will likely lead to an upward bias of the returns to ICT skills estimates, the direction of the omitted-variable bias is a prior not clear.

To solve these endogeneity problems, we apply two instrumental-variable (IV) strategies. The basic idea behind both is that individuals acquire ICT skills through learning-by-doing, and that the chance and duration of this learning increases when access to broadband Internet is technically available. It is important to note that both strategies identify variation in ICT skills that mainly comes from the initial phase of extensive broadband diffusion in the early 2000s. Over time, initial differences in broadband availability across countries and also across regions within countries were significantly reduced as lagging countries often massively supported investment in broadband infrastructure (e.g., Broadband Strategy of the German government). Moreover, new technologies allowing to access the Internet, e.g., via mobile broadband infrastructure, emerged in recent years. In the early phase, the Internet was mainly used to engage in email conversations and to locate and access digital information (*Web 1.0*). Internet use going beyond the mere consumption of content (e.g., podcasting, blogging, social networking) prevailing in the second half of the 2000s is less likely to contribute to the learning-by-doing effects we identify.

3.1 Cross-Country Instrumental-Variable Strategy

Our first IV strategy exploits exogenous variation in the probability of having access to broadband Internet across countries. This variation stems from the extent of preexisting fixed-line voice-telephony networks that were upgraded to provide fast Internet access by means of the so-called DSL technology. DSL relies on the copper wire of the voice-telephony network connecting households with the main distribution frame (MDF). In countries where fiber is rolled out directly to homes, the existing ducts of traditional voice-telephony networks are used to reduce the deployment cost of broadband. This means that the existing voice-telephony infrastructure initially built for purposes other than the provision of broadband is a necessary precondition for economically viable widespread diffusion of broadband Internet. Therefore, this infrastructure exogenously determines fixed-line broadband rollout in a country.[20]

The idea of using the extent of the traditional voice-telephony network as a source of exogenous variation in the availability of broadband Internet was introduced by Czernich, Falck, Kretschmer, and Woessmann (2011). They show that countries with a farther-reaching voice-telephony network in 1996 (i.e., before the introduction of broadband Internet in any country) had higher diffusion rates of broadband Internet in any consecutive year. Specifically, the authors estimate nonlinear diffusion curves where the maximum reach of broadband is given by the spread of the voice-telephony networks that existed before broadband was introduced:

$$B_{ct} = \frac{\gamma_c}{1+\exp[-\lambda(t-\tau)]} + \theta_{ct}, \tag{2}$$

where B_{ct} is the diffusion of broadband in the population of country c at time t. γ_c determines the country-specific maximum penetration level of broadband diffusion (ceiling). λ and τ denote the diffusion speed and the inflexion point of the diffusion process, respectively. Neither variable is country specific. θ_{ct} is a stochastic error term. γ_c is explained by the extent of the preexisting voice-telephony network, T_c , which can be upgraded to provide broadband Internet access. Thus, γ_c can be written as:

$$\gamma_c = \delta_0 + \delta_1 T_c. \tag{3}$$

Figure 2 plots the actual and estimated broadband internet diffusion curves across the 19 countries in our sample. To construct the figure, we used ITU data containing the number of broadband subscribers per inhabitant in the period 1996 to 2012 and the number of telephone access lines per inhabitant, that is, the voice-telephony penetration rate, in 1996.[21] The figure reveals that the estimated broadband Internet diffusion based on Equations (2) and (3) is generally very close to the actual diffusion. However, in some countries, such as Korea, the preexisting voice-

[20] Before the introduction of the DSL technology, only low-speed Internet access via dial-up-type technologies such as modems and ISDN was feasible via the voice-telephony network. Even in the best case of high-end ISDN access, the maximum available speed was 128 kbit/s. In the early days of DSL technology, DSL subscriptions of at least 256 kb/s were marketed by telecommunication carriers. However, the bandwidth rapidly increased over time due improvements in DSL technology. These improvements dramatically reduced limitations to Internet use as well as excessive waiting times for a response from the Internet.

[21] The International Telecommunications Union (ITU) is the U.N. agency for telecommunications.

telephony network does not capture actual broadband penetration well. In Korea, the government heavily subsidized the rollout of fiber to homes, resulting in a faster broadband penetration than predicted. Similarly, in Norway, we observe that actual broadband diffusion was faster than predicted diffusion toward the end of the observation period because of a public program progressively installing broadband access points. Such state intervention is likely not independent of a country's economic development; in fact, investments in speeding up the rollout of broadband Internet were typically at the heart of economic stimulus packages introduced in the aftermath of the economic crisis in 2008 and 2009 (OECD, 2009). Using only the predicted speed of broadband diffusion determined by the extent of the preexisting voice-telephony network solves these endogeneity problems.

<< Figure 2 about here >>

Following the above reasoning, we argue that individuals living in countries with a farther-reaching voice-telephony network in 1996 were more likely to have early access to broadband Internet, thus increasing their chances and duration of accumulating ICT skills through learning by doing until 2011/2012 (i.e., the time of the PIAAC survey). We implement this cross-country 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:

$$ICT_{ic} = \alpha_0 + \alpha_1 T_c + \boldsymbol{X_{ic}\alpha_2} + \boldsymbol{X_c\alpha_3} + \vartheta_{ic}. \tag{4}$$

The main worry with this identification strategy is the possibility that preexisting fixed-line networks affect wages today, either directly or through a channel other than ICT skills. To dispel concerns about the exogeneity of our instrument, the vector $\boldsymbol{X_c}$ contains a country's GDP-per-capita level before broadband rollout and country-level wages today. Conditioning our IV estimations on the historical GDP per capita captures any direct positive economic effect of the voice-telephony network until the emergence of broadband Internet (Röller and Waverman, 2001). Including this variable also controls for the fact that richer countries had a better-developed fixed-line infrastructure prior to broadband rollout and pay higher wages today.

Further accounting for a country's current wage level controls for country trends in wages from the pre-broadband period to today that might be correlated with a country's technological state and, thus, also with historical voice-telephony diffusion. Such trends in wages might arise from the (country-level) concentration of firms that were not only early adopters of ICT but also of other productivity-enhancing technologies. Such concentrations can be explained by a country's culture and institutions leading to the prevalence of certain management practices, work organization, or labor relations. Moreover, a growing body of evidence suggests that high-speed Internet has enabled productivity advances that accelerate economic growth (Czernich, Falck, Kretschmer, and Woessmann, 2011) and increase wages (Forman, Goldfarb, and Greenstein, 2012).[22] Adding average wages accounts for these direct productivity-enhancing effects of high-speed Internet availability, and we effectively identify returns to ICT skills based on the difference between an individual's wage and the country mean.[23]

Another concern is that the instrument is just spuriously correlated with country-level variables that also affect ICT skills (such as labor-market institutions or quality of the education system). Therefore, Section 4.1 provides a careful analysis showing that the instrument influences different groups of people within the same country differently, and it does so in a way that is consistent with a learning-by-doing channel.

3.2 Within-Country Instrumental-Variable Strategy

While our international data allow us to consider much wider variation in the extent of fixed-line networks than exists in a single country, they come at the cost of relying on limited degrees of statistical freedom (effectively dealing with 19 independent observations). We thus complement our cross-country analysis with within-country evidence on the returns to ICT skills in Germany, again using exogenous variation in the deployment of broadband infrastructure as an instrument for ICT

[22] However, the results in Forman, Goldfarb, and Greenstein (2012) suggest that the impact of high-speed Internet on wage growth is modest. Using U.S. county-level data, the authors find that investment in the Internet is correlated with wage growth in only about 6 percent of U.S. counties. Interestingly, these counties were already well-performing before high-speed Internet diffusion took off.

[23] Data on GDP per capita in 1996 are provided by the OECD. We calculate a country's current wage level directly from the PIAAC data, using only wages from workers aged 50 to 59, which are not included in our estimation sample (see Section 4.1). We thus avoid capturing a simple mechanical correlation of individual wages and a country's mean wage. We omit from our sample workers from age 60 onward because of differences across countries in retirement and labor-force participation rates.

skills. However, 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 level, educational attainment, and degree of urbanization. Since these factors may also affect current wages, our within-country IV strategy uses technical peculiarities of the traditional voice-telephony network that hindered broadband Internet access for many German regions.[24] 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 with the declared goal of providing universal telephone service to all German households. In traditional telephone networks (see Figure A-2), the length of the so-called last mile, that is, a pair of copper wires reaching from every household to the assigned MDF, is irrelevant for the quality of the service. In contrast, in a DSL network, which is the dominant broadband technology in Germany, the last-mile distance plays a crucial role because the maximum bandwidth depends on the length of the copper wire between the household and the MDF. Below the threshold of about 4,200 meters (2.6 miles), DSL subscriptions at a minimum downstream data transfer rate of 384 kb/s were offered. Past this threshold, however, DSL technology is no longer feasible and parts of the copper wire (typically placed between the MDF and street cabinet) must be replaced with fiber wire to provide DSL. 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.[25]

We follow Falck, Gold, and Heblich (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 next MDF and merge this information, as well as information on the technological availability of DSL, with the German PIAAC data.[26] Following a similar line of argumentation as in the cross-

[24] Other studies have used variation in technical broadband availability across locations as an exogenous source of variation in actual use (Bertschek, Cerquera, and Klein, 2013). However, this instrument is valid only conditional on structural location characteristics that determine the investment decisions of telecommunication carriers. Bhuller, Havnes, Leuven, and Mogstad (2013) and Akerman, Gaarder, and Mogstad (2015) exploit variation in the timing of broadband deployment across locations in Norway with the variation in timing due to limited funding of a public program (see Section 3.1) and not based on the decisions of profit-maximizing telecommunication carriers.

[25] The costs of rolling-out one kilometer of fiber wire subsurface amount to 80,000 euro, with an additional 10,000 euro to install a new node where the remaining part of the copper wires is connected to the fiber wire (Falck, Gold, and Heblich, 2014).

[26] Availability of DSL is measured as the percentage of households in a municipality for which DSL is technologically feasible. Data are taken from the German Broadband Atlas, commissioned by the German Federal Ministry of Economics, where telecommunication operators self-report the number of households that are covered by their networks at a minimum downstream data transfer rate of 384 kb/s.

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.

In an extension, we narrow the sample even further and focus on municipalities without an own MDF. While 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 to host an MDF at the time the voice-telephony network was being 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, thus allowing them to access broadband Internet. This provides variation in the instrument in the restricted sample. However, the size of this restricted sample is considerably smaller than that of the full sample because the sampling of municipalities in PIAAC was proportional to municipality size (Rammstedt, 2013).

Similar to the cross-country models, we control for potential direct effects of broadband diffusion on wages by including average wages of individuals in a municipality who are aged 50–59 years. We also account for the municipality's economic situation and its age composition by adding the unemployment rate and the population share of individuals above 65 years, respectively, as control variables.[27]

However, an important threat for the validity of our within-country IV strategy would be if people selectively relocate from dwellings at a distance to the MDF above the 4,200-meter-threshold to dwellings below the threshold. To assess this issue, we employ annual household survey data from the German Socio-Economic Panel (SOEP) (Wagner, Frick, and Schupp 2007). We use the

[27] We drop Berlin from our analysis because we are unable to distinguish between former West and East Berlin in terms of DSL availability. We also maintain the sample restrictions from the cross-country analysis, i.e., we include only employees aged 20–49 and drop first-generation migrants. Data on GDP per capita in 1996 are not available at the municipality level, so we are unable to add this information in our within-country estimations. To account for the fact that wage setting at the regional level in Germany can be affected by economic conditions and the age structure, our estimations account for the unemployment rate and the population share of individuals above 65 years. Data come from the German Federal Statistical Office.

exact geo-coordinates[28] of the SOEP households in West Germany (excluding Berlin) for the survey waves 2000–2010 to calculate whether a household has changed its distance to the MDF between two survey waves; that is, we can identify moves at a very small regional scale (including moves within the same neighborhood). 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 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 from dwellings being situated below the threshold. The average relocation rate for households who lived in dwellings above the threshold is slightly—and insignificantly—lower at 6.2 percent. Furthermore, 93.8 percent of the relocations do not involve a crossing of the threshold. In summary, this relocation pattern is clearly not in line with any sorting related to broadband Internet access.

Throughout, we cluster standard errors at the level where the instrument varies (Moulton, 1986, 1990); that is, standard errors are clustered at the country level in the cross-country analysis and at the municipality level in the within-country analysis.[29] Moreover, our estimations always employ the sample weights provided in PIAAC; 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.

4. Cross-Country Estimation Results

4.1 Sample Selection and Instrument Validity

It is paramount for the validity of our identification strategy that the instrument explains ICT skills only for the part of the country population that can potentially be affected by the instrument.

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

[29] Recent research has shown that clustered standard errors can be biased downward in samples with a small number of clusters (e.g., Donald and Lang, 2007; Cameron, Gelbach, and Miller, 2008; Angrist and Pischke, 2009; Ibragimov and Muller, 2010; Imbens and Kolesar, 2012). Although there is no widely accepted threshold when the number of clusters is "small", the work of Cameron, Gelbach and Miller (2008), Angrist and Pischke (2009), and Harden (2011) suggests a cutoff of around 40 clusters. To see whether clustering in our cross-country sample with just 19 clusters produces misleading inferences, we use the wild cluster bootstrap procedure suggested by Cameron, Gelbach and Miller (2008) for improved inference with few clusters (we used Stata's *cgmwildboot* command for implementation). All results remain robust when employing the wild bootstrap procedure as an alternative to clustering.

Otherwise, it may just be spuriously correlated with ICT skills. Since the instrument basically reflects the technically determined availability of broadband Internet in a country in the first decade of the 2000s, it should primarily affect the ICT skills of individuals who most likely used the Internet during this decade.

As a first check, we investigate the relationship between ICT skills and traditional fixed-line diffusion by migration status. While natives and second-generation immigrants most likely have lived in the PIAAC test country during the first decade of the 2000s, this is not certain for first-generation migrants. We thus expect to find a positive first-stage relationship for the first two groups, while the relationship should be considerably weaker or nonexistent for first-generation immigrants. Table 1 shows the expected positive first-stage relationship for natives and second-generation immigrants.[30] For first-generation immigrants, however, fixed-line diffusion and ICT skills are not significantly related.[31] Consequently, we exclude first-generation immigrants from the subsequent analyses.

<< Table 1 about here >>

We also expect that our first-stage relationship should be strongest for individuals who were old enough to use the Internet in the first decade of the 2000s, but still young enough to be open to this new technology. Figure 3 shows the first-stage relationship for various age groups and, indeed, the figure reveals that fixed-line networks in 1996 especially influence the ICT skills of persons between 20 and 49 years of age. Although there is some variation, ICT skills of persons in this age range are very similarly affected by preexisting fixed-line networks. However, we observe a strong decline in the effect of our instrument for age groups beyond age 49 and for the very young age group of individuals aged 16–19, who are likely to use technology other than DSL to access the Internet (e.g.,

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[30] We only report specifications with all control variables included. See below for models where we include control variables successively.

[31] Interestingly, the association between ICT skills and all other control variables is very similar across the three groups, indicating that the accumulation of ICT skills generally follows similar patterns for natives and both migrant types.

LTE/HSPA on smartphones).[32] These results provide a rationale for restricting our main estimation sample to 20–49 year olds.[33]

<< Figure 3 about here >>

Since our instrument relies on between-country variation, our first-stage relationship may be driven by some country outliers, which could cast doubt on the external validity of our results. Figure 4 shows an added-variable plot for our first-stage regression with all control variables. To construct this graph, we aggregated the residuals of the individual-level regressions to the country level, the level where the instrument varies. The figure reveals that the positive relationship between our instrument and ICT skills is evident across the entire sample.[34]

<< Figure 4 about here >>

4.2 OLS and IV Estimations

We now turn to our two-stage least squares results, which are reported in Columns (4)–(6) of Table 2. For comparison, Table 2 also contains the results from corresponding OLS estimations (Columns (1)–(3)). As outlined above, we restrict our sample to natives and second-generation immigrants between 20 and 49 years of age. The table also reports the first-stage coefficient on preexisting fixed-line diffusion and the *F*-statistic on the excluded instrument. In line with the evidence presented in Section 4.1, the instrument is a strong predictor of ICT skills. In the most demanding specification with all control variables (Column (6)), the *F*-statistic is 55.7 and thus well above the threshold for a strong instrument. The first-stage estimate suggests that increasing the

[32] In Section 4.4, we show that our results continue to hold when we control for Internet access technologies other than DSL.

[33] We also performed estimations for other age groups (35–54, 35–65, 16–65), yielding qualitatively similar results to those reported below.

[34] Excluding the two extreme observations (Ireland and Sweden) leads to a similar regression line, with only a slightly flatter slope.

voice-telephony penetration rate from 0 to 100 percent is associated with an increase in ICT skills of about 11.6 country-level standard deviations (98 points). Although this appears to be a very large effect, note that the diffusion of fixed-line networks in 1996 effectively varies only between 17 percent (Poland) and 68 percent (Sweden) (see Table A-2). Our first-stage estimate thus suggests that an increase in the diffusion of fixed-line networks from the minimum to the maximum value in the sample is associated with an increase in ICT skills of 49 points.[35]

The second stage shows the effect on wages of an increase in ICT skills induced by preexisting fixed-line networks. We begin by showing a specification that only controls for GDP per capita in 1996 and today's average wage level in a country, and then stepwise add further individual-level control variables.[36] Across specifications, our results indicate significant returns to ICT skills. With all controls (Column (6) of Table 2), the ICT-skill coefficient of 0.075 implies that a one standard deviation increase in ICT skills attributable to a historically larger fixed-line network leads to a 7.5 percent increase in wages.[37] As compared to the corresponding OLS coefficients, the estimated returns to skills in the IV models tend to be somewhat smaller, but OLS and IV estimates are almost equal in the specification with all controls.[38] While all the individual-level control variables enter the regressions with the expected sign[39], the IV coefficient is little affected by their inclusion, indicating that the variation in ICT skills captured by the instrument is not systematically related to an individual's work experience, gender, or education level.

To get a sense for the magnitude of this estimate, note that one standard deviation in ICT skills is similar to the difference in average ICT skills between Finland and Germany or between Denmark and the United States. Likewise, one standard deviation in ICT skills is also roughly similar to skill

[35] Table A-3 reports all first-stage coefficients for the corresponding specifications in Table 2, Columns (4)-(6). We observe that, on average, women have lower ICT skills than men and that ICT skills decrease with work experience. Not surprisingly, more educated workers also tend to have higher ICT skills. Assuming positive returns to ICT skills, the negative correlation between ICT skills and the average wages of the elderly workforce (who typically have low ICT skills) is also plausible.

[36] In Section 4.4., we account for additional country-level and individual-level control variables.

[37] All results are robust to using country-level aggregates of ICT skills instead of individual-level skills. We also experimented with aggregating all variables to the country level, and found the results to be robust. OLS results of cross-country regressions (with and without control variables) are plotted in Figure A-3.

[38] OLS estimates of the returns to skills are very similar when including country fixed effects. This indicates that the country-level control variables capture the most relevant level differences in wages across countries. [39] The coefficient on GDP per capita is negative when the average wage level is also included, but it has the expected positive sign without the wage control.

[39] The coefficient on GDP per capita is negative when the average wage level is also included, but it has the expected positive sign without the wage control.

difference between ICT professionals (the occupation with highest average ICT skills) and administrative and commercial managers within the United States, and is only slightly larger than the difference between ICT professionals and science and engineering professionals. It is also useful to compare the magnitude of our returns to ICT skills coefficient with existing estimates on the returns to cognitive skills. In their sample of prime-age, full-time employed workers, Hanushek, Schwerdt, Wiederhold, and Woessmann (2015) find returns to numeracy skills of 10.2 percent in a specification analogous to ours (see pooled model in their Table 4); returns are very similar for literacy skills.[40] Although these estimates cannot be interpreted causally, this is at least suggestive evidence that ICT skills as measured in PIAAC are somewhat less valued in the labor market than more traditional cognitive skills.

<< Table 2 about here >>

It is important to note that our IV approach is a reduced-form analysis of the following three-stage model: (1) fixed-line diffusion in 1996 predicts broadband Internet diffusion in 2012; (2) broadband Internet diffusion predicts ICT skills; and (3) ICT skills predict wages. To show that the expected relationship holds at each stage, we estimate a recursive system of three equations using a seemingly unrelated regressions model. Results shown in Table A-4 imply that preexisting fixed-line diffusion is positively associated with the availability of broadband Internet today (first equation). In the second equation, we find that Internet diffusion is positively related to ICT skills, which in turn significantly predict wages in the third equation. Strikingly, the estimated returns to ICT skills in these models are very similar to the 2SLS estimation results in Table 2.

4.3 Placebo Tests

To interpret the above IV results as showing a causal effect of ICT skills on wages, we need to be certain that the spread of voice-telephony networks that existed before the emergence of broadband Internet insulates the effect of ICT skills on wages from that of other skills. Thus, in our

[40] The returns-to-skills estimates remain almost unchanged when we re-estimate their model for the 19 countries in our sample.

first-stage regression, we replace ICT skills with numeracy and literacy skills, respectively, which are also available in the rich PIACC dataset. If our instrument does indeed isolate the effect of ICT skills, it should not be systematically related to numeracy and literacy skills. Table 3 shows the results of these placebo tests. As long as we do not control for ICT skills, the instrument is also positively associated with numeracy and literacy skills due to the high correlations between the different skill domains (Columns (1) and (2)); still, ICT skills are more strongly affected by the instrument than are the other skill domains (Column (3)). Importantly, once we control for ICT skills, we find that neither numeracy nor literacy skills are significantly related to the preexisting fixed-line network (Columns (4) and (5)). We consider this as strong evidence that our instrument captures the "right" variation: Reassuringly, the instrument continues to be a relevant predictor of ICT skills when the other skill domains are accounted for (Columns (6) and (7)).

However, we prefer not to control for numeracy or literacy skills in the IV regressions because how fast a person accumulates ICT skills likely depends on his or her literacy and numeracy skills, for example, because acquiring and evaluating ICT-related information (which is a considerable part of ICT skills) is facilitated by high reading ability. Thus, controlling for other skill domains in the regressions would disregard one important mechanism through which ICT skills develop.[41]

<< Table 3 about here >>

4.4. Robustness

An important concern with our IV strategy is that the extent of the pre-existing fixed-line network just picks up factors at the country level that influence individuals' wages, which are not captured by the included country level controls. One test whether our estimates reflect returns to ICT skills vis-à-vis returns to some unobserved country factors is to estimate the specifications within occupations which do not require ICT skills to fulfill the tasks associated with the job. The PIAAC background questionnaire provides information about the frequency of using software, programming language, and spreadsheet tools, which we aggregate into a single index of computer use at work.[42] Judging by this index, workers in elementary occupations[43] make least use of

[41] Still, returns-to-skills estimates remain statistically significant and sizeable when including numeracy or literacy skills as an additional control.

[42] Specifically, PIAAC respondents were asked to indicate how often they perform the following activities at work: create or read spreadsheets, use word-processing software, use programming language, and engage in computer-aided

computers, so we would expect that returns to ICT skills are small or even nonexistent there. The estimation results substantiate this conjecture: the IV-coefficient on ICT skills fails to capture statistical significance in a sample of workers in elementary occupations. This result cannot be explained by (i) a weak instrument—the first-stage *F*-statistics is 19.2 in this restricted sample; (ii) insufficient variation in ICT skills in elementary occupations; or (iii) the fact that returns to skills are generally small in elementary occupations; in fact, returns to numeracy skills in these occupations are only slightly below the average return in all other occupations.

Furthermore, in Tables 4 and 5, we present a series of robustness checks designed to test the sensitivity of our main results to adding further controls and to changes in the estimation sample. In our baseline specification, we controlled for a country's GDP per capita in the pre-broadband period and its overall wage level today. However, it could be argued that fixed-line diffusion in 1996 is correlated with other country-level factors that also affect an individual's wage and that are not captured by the two included country-level controls.[44] First, we add control variables characterizing the labor market, namely, union density, employment protection legislation, public-sector share, and youth unemployment rate. We also account for a country's industry structure by including the GDP share of the service sector. The available human capital is proxied by the share of persons currently enrolled in tertiary education: Finally, we add the extent of the preexisting TV-cable network, which has been upgraded for broadband Internet use in many countries (Czernich, Falck, Kretschmer, and Woessmann, 2011), and current cellphone diffusion to proxy for Internet access technologies other than DSL.[45] The results, shown in Columns (1) to (8) of Table 4, demonstrate that the estimated

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real-time discussions. To create a summary index, we follow Kling, Liebman, and Katz (2007) and first calculate the *z*-score for each of the variables individually, aggregate the z-scores, and normalize by the standard deviation of the aggregate. Note that all calculations are performed for each country individually to account for possible differences in answering behavior.

[43] Elementary occupations include cleaners and helpers, agricultural, forestry and fishery laborers, laborers in mining, construction, manufacturing and transport, food preparation assistants, street and related sales and service workers, refuse workers, and other elementary workers.

[44] Given that variation in our IV specification comes from differences in the fixed-line diffusion across 19 countries, degrees of freedom for adding further country-level controls are somewhat limited. We therefore include additional country-level controls one at a time.

[45] Data on union density and employment protection legislation are provided by the OECD and refer to 2011 unless otherwise noted. Union density refers to 2009 in the Czech Republic and to 2010 in Denmark, Estonia, and Poland. The employment-protection indicator is the weighted sum of sub-indicators concerning the regulations for individual dismissals (weight of 5/7) and additional provisions for collective dismissals (2/7), incorporating 13 data items (for details, see Venn, 2009). Data on TV cable diffusion in 1996 are taken from ITU. All remaining variables refer to 2012. Service-sector shares are provided by the World Bank and Statistics Canada. The share of persons enrolled in tertiary education is provided by the UNESCO Institute for Statistics. For Canada, we constructed the share of persons enrolled in tertiary education by dividing the total number currently in tertiary education (taken from Statistics Canada)

returns to ICT skills remain very similar when including additional country-level controls. Unreported regressions show that the results continue to hold when we add gross fixed capital formation or the number of patents registered at the European Patent Office (either all or only ICT-related patents) to capture a country's technological structure.[46]

Another potential concern is that our effects are driven only by those countries with very low levels of both broadband diffusion and wages. Closer inspection of the data revealed that the four post-communist countries in our sample (the Czech Republic, Estonia, Poland, and the Slovak Republic) had the lowest fixed-line diffusion in 1996 and also paid the lowest wages in 2012 (see Tables A-1 and A-2). It is therefore reassuring that the coefficient on ICT skills remains very similar when omitting the post-communist countries from the sample (Column (9) of Table 4).[47]

<< Table 4 about here >>

In Table 5, we assess the robustness of our baseline results to the inclusion of additional individual-level control variables. First, it may be argued that actual work experience is endogenous to skill levels because people may use and reinforce skills on the job. Actual work experience may thus capture a channel of the effect of skills on wages. Therefore, in Columns (1) and (2) we replace actual work experience by age and potential work experience (age minus years of schooling minus six), respectively. Likewise, full-time jobs may be more likely to sustain skill levels by requiring more regular practice of them or by providing the money to invest in professional development and adult education. Thus, whether a person is full-time employed may be an important omitted variable in the baseline specification. In Column (3), we control for a full-time employment indicator.[48] Further,

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by population size (taken from the OECD). The youth unemployment rate is provided by the OECD. The public-sector share is calculated from the PIAAC data.

[46] Data on gross fixed capital formation are provided by the OECD and data on (ICT) patents are provided by Eurostat. Data always refer to 2012.

[47] Similarly, results are robust to excluding the Nordic countries (Denmark, Finland, Norway, and Sweden), which perform best in the ICT skills assessment and also pay the highest wages. Specifications that restrict the analysis to European countries only or that include continental fixed effects also lead to very similar results.

[48] Full-time employment is defined as working at least 30 hours per week. In Australia and Austria, full-time working status is based on a question asking whether a respondent works full-time. Since the Canadian data neither

if family background is related to skill development and family ties help people find better jobs, the association between skills and wages will be confounded. Column (4) captures the influence of parental background by controlling for parental education.[49] Similarly, a person's health may positively affect both skill acquisition and wages. Column (5) thus controls for a measure of self-assessed health status available in PIAAC. Column (6) controls for the size of the firm in which the PIAAC respondent is working, capturing differences in the firm-size distribution across countries that may affect the returns-to-skills estimates. Finally, we add controls for 10 one-digit occupation (ISCO) categories (Column (7)) and 21 one-digit industry (ISIC) categories (Column (8)), which account for differences in wages across occupations and industries. Neither of these additional control variables qualitatively changes the baseline results.

<< Table 5 about here >>

Taken together, the evidence provided in Tables 4 and 5 strongly suggests that our IV strategy did indeed identify variation in ICT skills that is independent of potentially omitted variables at the country or individual level.[50]

5. Within-Country Estimation Results

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—which allows us to exploit historical peculiarities in the structure of the voice-telephony network as a source of plausibly exogenous

report working hours nor work status, we were unable to create an indicator for full-time employment in the Canadian sample.

[49] The negative coefficient on parental education indicates that conditional on an individual's educational attainment and his or her level of ICT skills, better parental education does not have an additional positive effect on wages.

[50] In unreported analysis, we explored whether the impact of ICT skills differs across various worker subgroups. We performed subsample estimations by gender and education level, and also estimated effects separately for private-sector and public-sector employees, and for workers in manufacturing and services. The sample splits reveal that returns to ICT skills are quite homogenous across the considered subgroups. The only exception is that ICT skills are less strongly rewarded in the public sector than in the private sector (3.2 percent vs. 8.9 percent). Results are available on request.

variation in ICT skills (see Section 3.2). In Table 6, 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 closest MDF above the threshold of 4,200 meters. In the full sample, shown in Columns (1)–(3), 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 (Column (3)), we find that persons in municipalities with a distant MDF have 59 percent of a standard deviation lower ICT skills than persons in municipalities with a close MDF. When we use the threshold instrument in a sample of less-agglomerated West German municipalities without an own MDF (Columns (4)–(6)), 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.[51] To address a potential weak-instrument problem (e.g., Bound, Jaeger, and, Baker 1995), we use LIML to obtain our IV estimates since LIML minimizes the coefficient estimate bias associated with weak instruments.[52]

Turning to the second stage of our IV estimation (see the upper part of Table 6), we find that a one standard deviation increase in ICT skills attributable to the technical threshold in broadband availability increases wages by 14 percent in the full sample (Column (3)). The coefficient is statistically significant at the 10 percent level. Estimated returns to skills even increase to 19 percent in the restricted sample, also significant at the 10 percent level (Column (6)).[53] The returns are somewhat larger than the corresponding estimate in the cross-country sample, which is consistent

[51] As shown in Section 3.2, estimations based on the German Socio-Economic Panel (SOEP) indicate that 7.3 percent of households living in dwellings below the 4,200-meter threshold change their location each year. This figure is not significantly different for households living in dwellings above the threshold (moving rate of 6.2 percent), suggesting that the first-stage effects are, if at all, attenuated due to classical measurement error.

[52] We also 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 biases the IV results in a meaningful way. Results are available on request.

[53] The three-equation estimations in Table A-5 indicate that the reduced-form first-stage estimates in Table 8 do indeed capture the effect of Internet availability on ICT skills. We find that municipalities above the 4,200-meter threshold have on average a 6 percentage point lower broadband availability (4 percentage points in the no own MDF sample), while broadband availability positively affects individual ICT skills. Reassuringly, wage returns in the three-equation estimations are very similar to those obtained in the IV models.

with the results in Hanushek, Schwerdt, Wiederhold, and Woessmann (2015) showing that Germany is one of the countries with the highest returns to cognitive skills worldwide.

<< Table 6 about here >>

Finally, to ensure that our within-country identification strategy insulates the effect of ICT skills on wages from the effect of general ability, Table 7 presents placebo tests analogous to those in Table 3 for the cross-country sample. While literacy skills are not systematically affected by the threshold instrument and numeracy skills even show significantly *positive* coefficients throughout specifications, ICT skills are consistently negatively affected by the instrument, even conditional on the other skill domains.

<< Table 7 about here >>

6. Task Content of Occupations and Returns to ICT Skills

In the following we will look at a potential mechanism driving the returns to ICT skills, which is the task content of jobs. The skill structure of developed economies has changed remarkably since the second half of the 20th century. Educational upgrading was a prevalent trend and much evidence points toward increases in skill premia (e.g., Goldin and Katz, 2009) and increases in wage inequality (e.g., Autor, Katz, and Kearney, 2008; Dustmann, Ludsteck, and Schönberg, 2009).[54] Along with these trends also came changes in the labor structure, investigated in numerous studies within the last three decades (e.g., Goldin and Katz, 1996, 2009; Acemoglu, 1998, 2003; Bresnahan, Brynjnolfsson, and Hitt, 2002). In particular, Autor, Levy, and Murnane (2003) relate changes in the U.S. labor structure since the 1960s to the proliferation of computers in the workplace. However, unlike previous studies, 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

[54] For a recent review, see Autor (2014).

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 and coordination). The underlying reasoning for this idea is that routine tasks embody explicit knowledge that can be relatively easily programmed, which is not the case for nonroutine tasks. Moreover, an increase—both qualitatively and quantitatively—in the supply of codifiable tasks increases the marginal productivity of employees who engage extensively in nonroutine tasks and who use routine work output as their work input.[55]

Trends toward a rising importance of these abstract tasks may be a potential mechanism behind our result that ICT skills are considerably rewarded in modern labor markets. If high ICT skills are required to obtain jobs that intensively use abstract tasks because these tasks are complementary to computers, any wage premia abstract jobs pay would imply positive returns to ICT skills. . To test this, we first assess the ICT skills of workers in occupations that make intense use of abstract (manual, routine) tasks and compare them to the ICT skills of workers with little abstract (manual, routine) task intensity.[56] We also investigate whether the proliferation of personal computers is complementary to abstract tasks and whether it substitutes for routine tasks. Specifically, we correlate abstract and routine task intensity, respectively, with the index of computer use at work introduced in Section 4.4. For this analysis, we gained access from the OECD to the two-digit ISCO-08 (International Standard Classification of Occupations) codes for all employed respondents in PIAAC, which we link to the measures of abstract, routine, and manual tasks from Goos, Manning, and Salomons (2014).[57]

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[55] Recent evidence suggests that such skill complementarity of personal computers is also present in Europe (Akerman, Gaardner, and Mogstad, 2015).

[56] Workers with the highest abstract job content are managers and teaching professionals. Occupations with the lowest abstract content are elementary occupations.

[57] They combine the five original DOT task measures of Autor, Levy, and Murnane (2003) into three task aggregates: (nonroutine) abstract tasks, routine tasks, and (nonroutine) manual tasks (see also Akerman, Gaardner, and Mogstad, 2015). The abstract task measure is the average of two DOT variables: "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." From these three measures, the Routine Task Intensity (RTI) index is constructed as

Figure 5 shows the results from this analysis. Both ICT skills and computer use systematically vary with jobs' task content. Using the population median to distinguish between jobs with high versus low task intensity, we observe in Panel A that workers in jobs requiring high abstract tasks have substantially stronger ICT skills than workers in occupations with low abstract task intensity (305 vs. 283 PIAAC points). In contrast, workers in jobs that are pervasive in routine or manual tasks have weaker ICT skills than their peers in jobs that involve few routine or manual tasks (routine: 290 vs. 297; manual: 288 vs. 298). Panel B reveals similar differences by job content when looking at our index of computer use at work. Computer use by workers in occupations requiring high abstract tasks is 35 percent of a standard deviation above the global mean and is 44 percent of a standard deviation below the mean for workers in occupations with little abstract task content. Not surprisingly, workers frequently performing routine or manual tasks are considerably less reliant on computers than are workers performing few of these tasks. For both ICT skills and computer use, the difference between occupations with high versus low task intensity is always largest for abstract tasks.[58] These results support the idea that the upsurge of computers in recent decades complements workers in executing nonroutine abstract tasks, and substitutes for workers performing routine and manual tasks.

<<Figure 5 about here >>

Motivated by these descriptive results, we estimate wage regressions that contain interactions between ICT skills (again instrumented by fixed-line diffusion in 1996) and the tasks performed at work. In addition to the baseline country-level and individual-level controls, all regressions also control for occupation fixed effects to rule out that our estimates are driven by cross-country

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the difference between the log of routine tasks and the sum of the log of abstract and the log of manual tasks. The task measures are mapped onto the ISCO occupational classification system and normalized to have mean zero and standard deviation one across occupations. See Autor, Levy, and Murnane (2003, Appendix 1) for examples of workplace activities with different task intensities.

[58] This result not only holds in the pooled sample, but also in each individual country. Moreover, differences in ICT skills and computer use between occupations with high versus low task intensity hardly change when we account for country fixed effects and also control for work experience, gender, and educational attainment.

differences in the occupational structure.[59] Standard errors are clustered at the country × occupation level, that is, the level where the interaction terms vary. The results are provided in Table 8. Columns (1) and (2) show that the wage premium to workers with higher ICT skills is smaller in occupations that heavily rely on computer use and abstract tasks, while only the interaction with abstract task intensity captures statistical significance. In terms of magnitude, the estimate in Column (2) implies that workers with abstract task intensity at the 75th percentile, as compared to workers at the 25th percentile of task intensity, earn a 2.8 percentage point lower wage increase for each one standard deviation increase in ICT skills. Results are similar when, in addition to abstract tasks, routine and manual tasks are included (Column (5)). However, neither an occupation's intensity of routine tasks (Column (3)), its intensity of manual tasks (Column (4)), nor its routineness (Autor and Dorn, 2013) are significantly related to the returns to ICT skills.[60]

<< Table 8 about here >>

Since our analysis focuses on the question of whether returns to ICT skills systematically vary with the task content of occupations, we can pursue an even more rigorous approach and include country fixed effects in addition to occupation fixed effects. Identification in this model comes only from variation within detailed country-occupation cells, so all factors that determine wages at the country level (e.g., labor-market institutions, economic policy, social norms, and political stability) are also taken into account.[61] The estimates, shown in Table A-6, are very similar to those without

[59] Due to the inclusion of occupation fixed effects, the main effects of the task measures are not identified in the wage regressions (the computer use index varies at the country × occupation level and is therefore identified). In regressions without occupation fixed effects, we find that, similar to Akerman, Gaardner, and Mogstad (2015), abstract and manual tasks are significantly positively related to wages and routine tasks are negatively (albeit not significantly) related to wages. Results are available on request.

[60] The first-stage results are omitted for brevity. However, the first-stage *F*-statistics, reported at the bottom of Table 8, indicate that the instruments are indeed relevant predictors of ICT skill and its interactions. Reassuringly, across specifications, the instruments always explain only variation in the "right" variable; i.e., past fixed-line diffusion does not explain the interactions between ICT skills and tasks, while the interaction between past fixed-line diffusion and tasks does not explain the main effect of ICT skills.

[61] While ICT skills are measured at the individual level and are thus not collinear to the country fixed effect, the instrument (past fixed-line diffusion) is absorbed by the fixed effect. Thus, we estimate the model without including ICT skills linearly. However, models using interactions between country-level ICT skills (which are perfectly collinear to the country fixed effects) and job task intensities show results very similar to those reported here.

country fixed effects. Specifically, the interaction between ICT skills and abstract task intensity retains a significantly negative coefficient and is of a similar order of magnitude as before. Moreover, the interaction between ICT skills and computer use at work also becomes significantly negative in this more demanding model (with a positive main effect), lending further support to the idea that computer use and abstract task content in an occupation are highly complementary.

Taken together, the results on the returns-to-skills interactions suggest that the wage gradient of ICT skills is systematically lower in occupations that are pervasive in abstract tasks. One explanation for this result is that workers with high ICT skills are overrepresented in these occupations due to the complementarity of computers (using and reinforcing ICT skills) and abstract tasks. Given the selection of individuals with high ICT skills into occupations that make intense use of these skills, marginal increases in ICT skills are not valued as highly as in other occupations. However, this negative interaction just reflects the intensive margin. Since wages in jobs that are dominated by abstract tasks are on average 25 percent higher than those for jobs that involve relatively few abstract tasks,[62] and since high ICT skills are presumably a necessary condition for obtaining these well-paid jobs, the (extensive margin) returns to ICT skills are likely substantial in jobs with a high abstract content.

7. Conclusion

This paper is the first to provide evidence on the labor-market returns to ICT skills by means of a novel dataset that measures individuals' ICT skills in 19 developed countries. We identify exogenous variation in ICT skills by exploiting the extent of traditional voice-telephony networks that were upgraded for fast Internet use in our sample countries. The underlying idea is that ICT skills are developed through learning by doing, for which Internet availability is a precondition. The instrument is a strong predictor of ICT skills, and a series of validity tests provide support for the existence of the learning-by-doing channel. Estimations additionally control for a rich set of individual-level and country-level variables, including a person's acquired level of schooling, general economic conditions before widespread broadband rollout, and a country's current wage level.

[62] This figure is obtained from a regression of log hourly wages on an indicator of whether a person works in an occupation with an above-median abstract task intensity, conditional on country fixed effects, a quadratic polynomial in work experience, gender, and years of schooling.

Our results indicate that better ICT skills are systematically related to higher wages. In the cross-country analysis, we find that a one standard deviation increase in ICT skills leads to a 7.5 percent increase in wages. A placebo test showing that preexisting fixed-line networks cannot explain any variation in numeracy or literacy suggests that our IV approach is able to insulate the wage effect of ICT skills from that of general ability. Returns to ICT skills are also sizable when we use a different source of identifying variation by exploiting technological peculiarities of the preexisting voice-telephony network in Germany that effectively excluded many municipalities from accessing high-speed Internet. These within-country results reveal that returns to ICT skills are especially pronounced for Germany.

By showing that ICT skills are quite substantially rewarded in the labor market, our results provide support for Neelie Kroes's notion of ICT skills as "the new literacy." Still, our findings should not be interpreted as conclusive evidence that ICT skills are valued more highly than other types of skills in modern knowledge-based economies. Providing such evidence would require identifying sources of variation that systematically capture other domain-specific skills that are not confounded by a person's general ability. However, given that evidence on the causal returns to cognitive skills (general or domain specific) has been rare thus far, we consider our work a suitable starting point for further inquiry into causality in the returns-to-skills estimation.

Our research is also relevant for the recent discussion about e-learning, that is, the use of ICT-based teaching methods as well as virtual learning technologies in the classroom and at home. The literature on how e-learning affects student achievement mostly suggests overall zero or very weak effects (for an overview, see Bulman and Fairlie, 2015), with positive effects only for some types of uses (Falck, Mang and Woessmann, 2015). However, there is evidence that e-learning helps develop ICT-related skills (Malamud and Pop-Eleches, 2011). Our results suggest that building ICT skills through e-learning, even if e-learning itself is not associated with better school grades, might prove beneficial for students' future labor-market outcomes.

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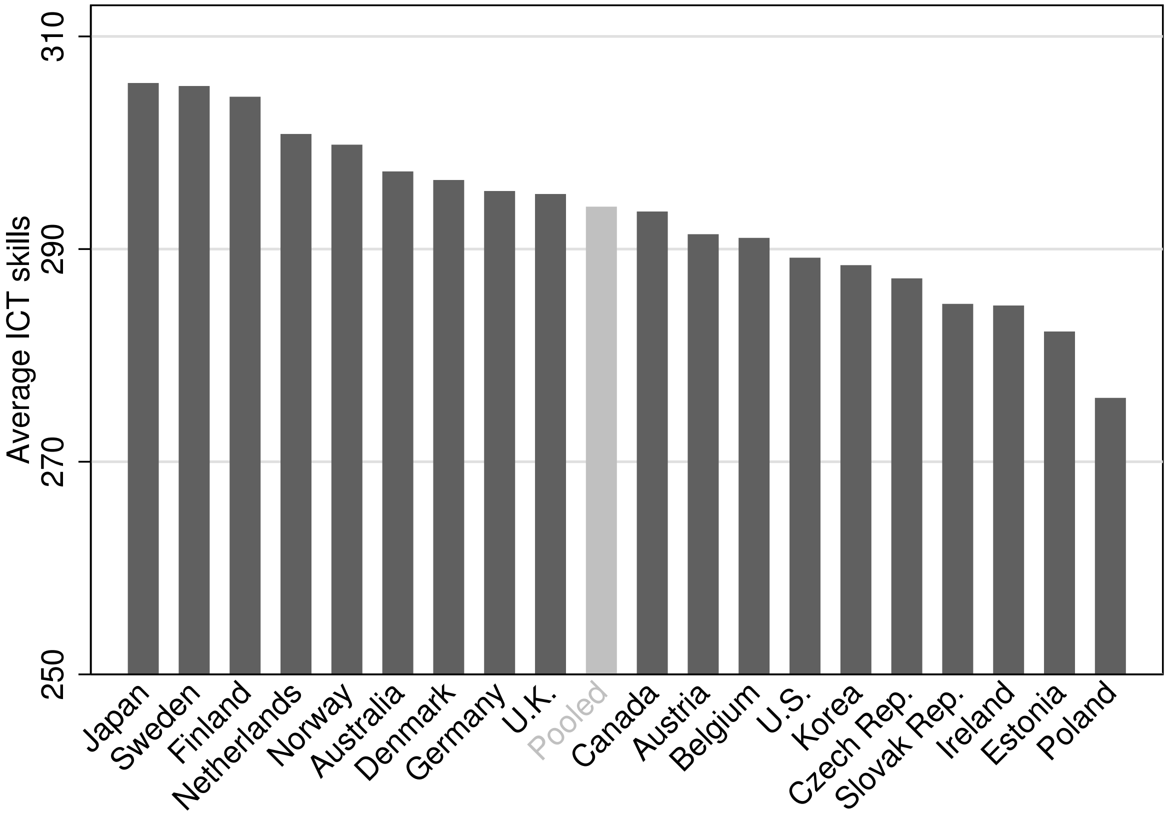
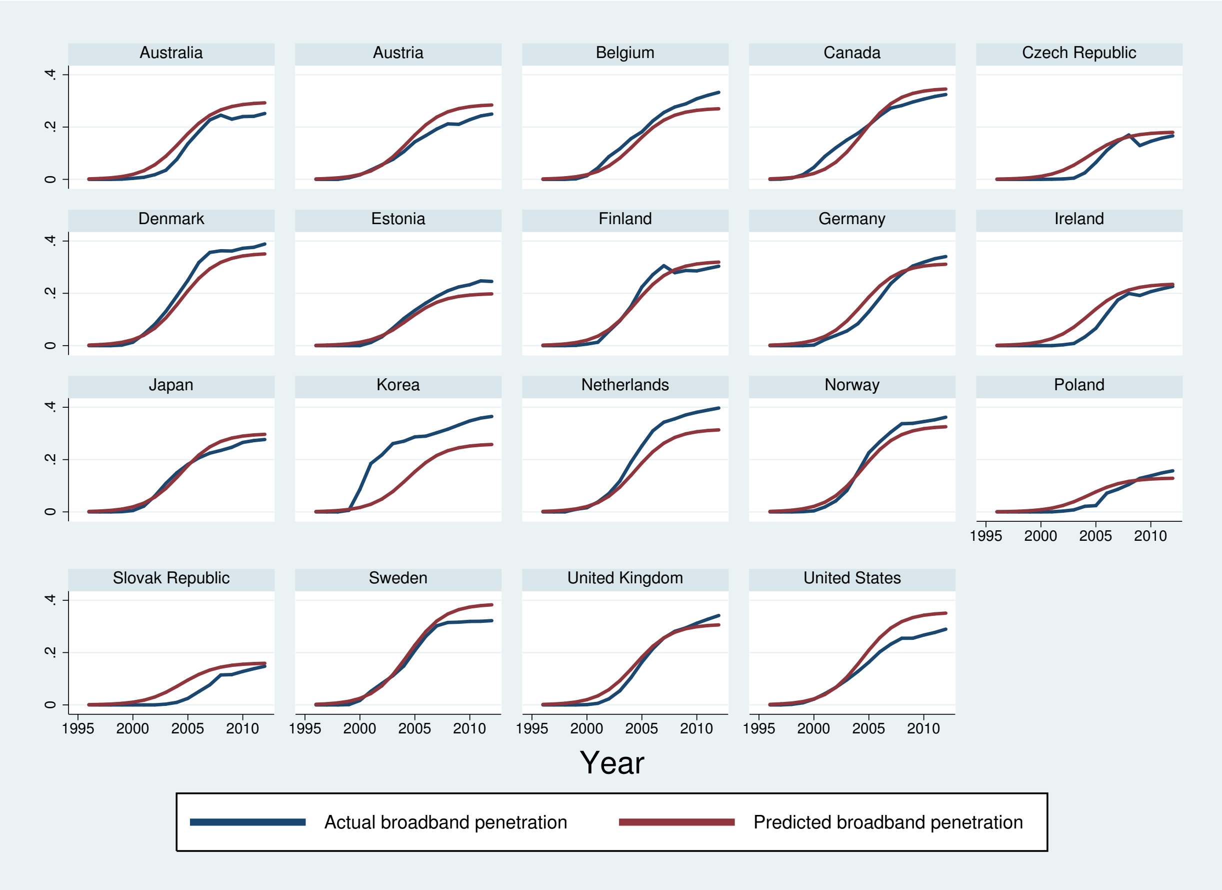
Figures and Tables

Figure 1: ICT Skills Around the World



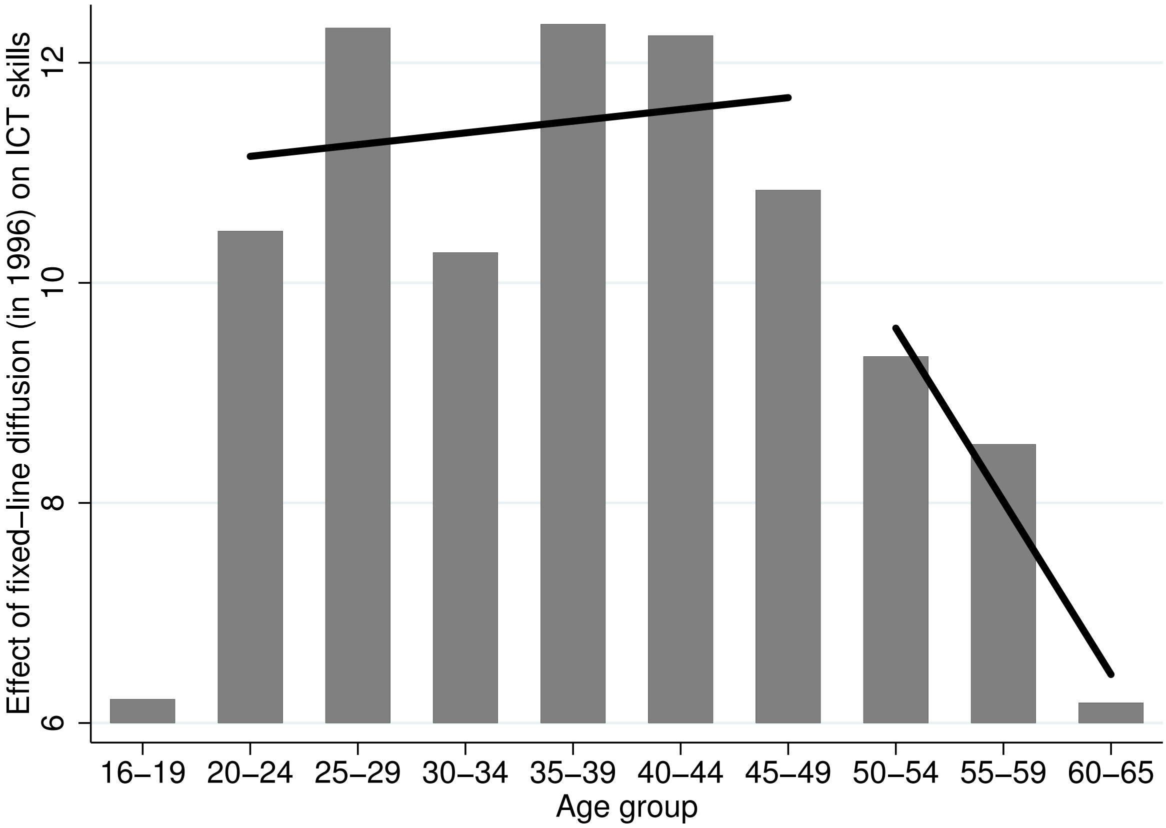
Notes: Average ICT skills across countries. Sample: employees aged 20–49 (no first-generation migrants). *Data source:* PIAAC.

Figure 2: Broadband Diffusion Across Countries: Actual and Predicted Curves, 1996–2012



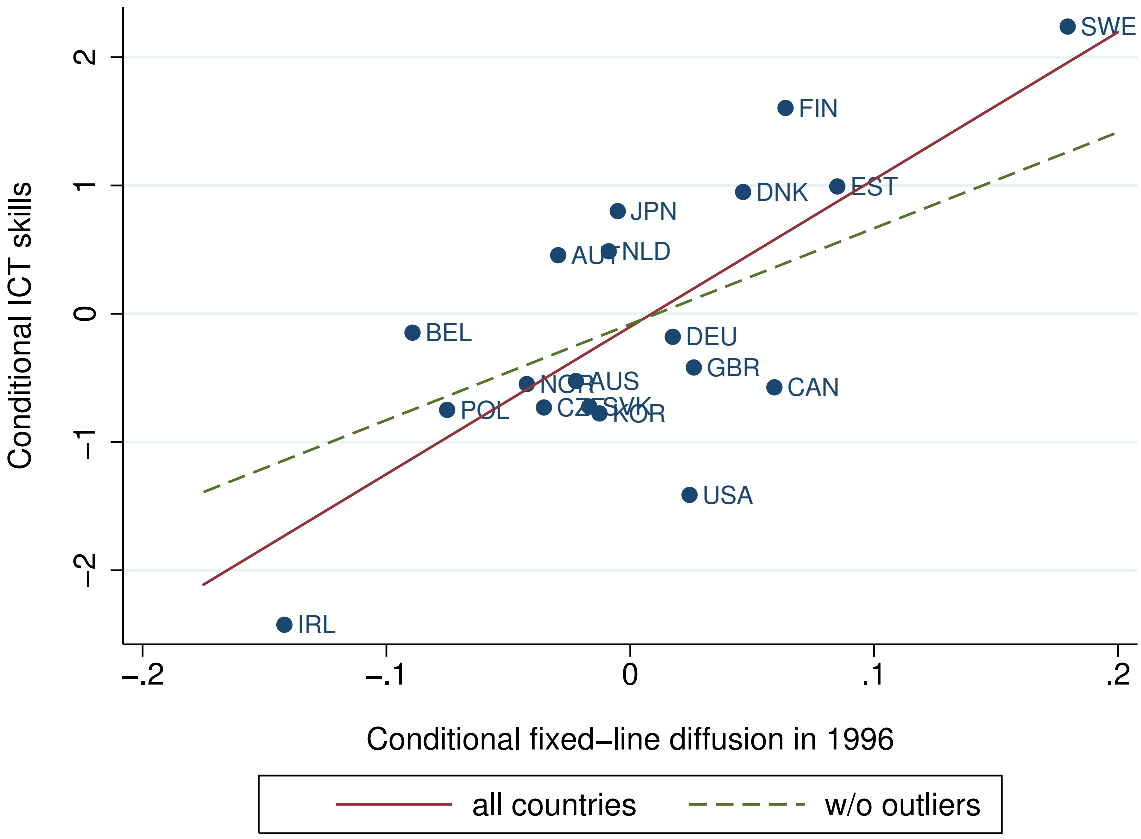
Notes: Predicted broadband diffusion is derived from nonlinear least squares estimation of a diffusion curve based on telephone access lines per 100 inhabitants in 1996. See Section 3 for details. *Data source:* ITU.

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



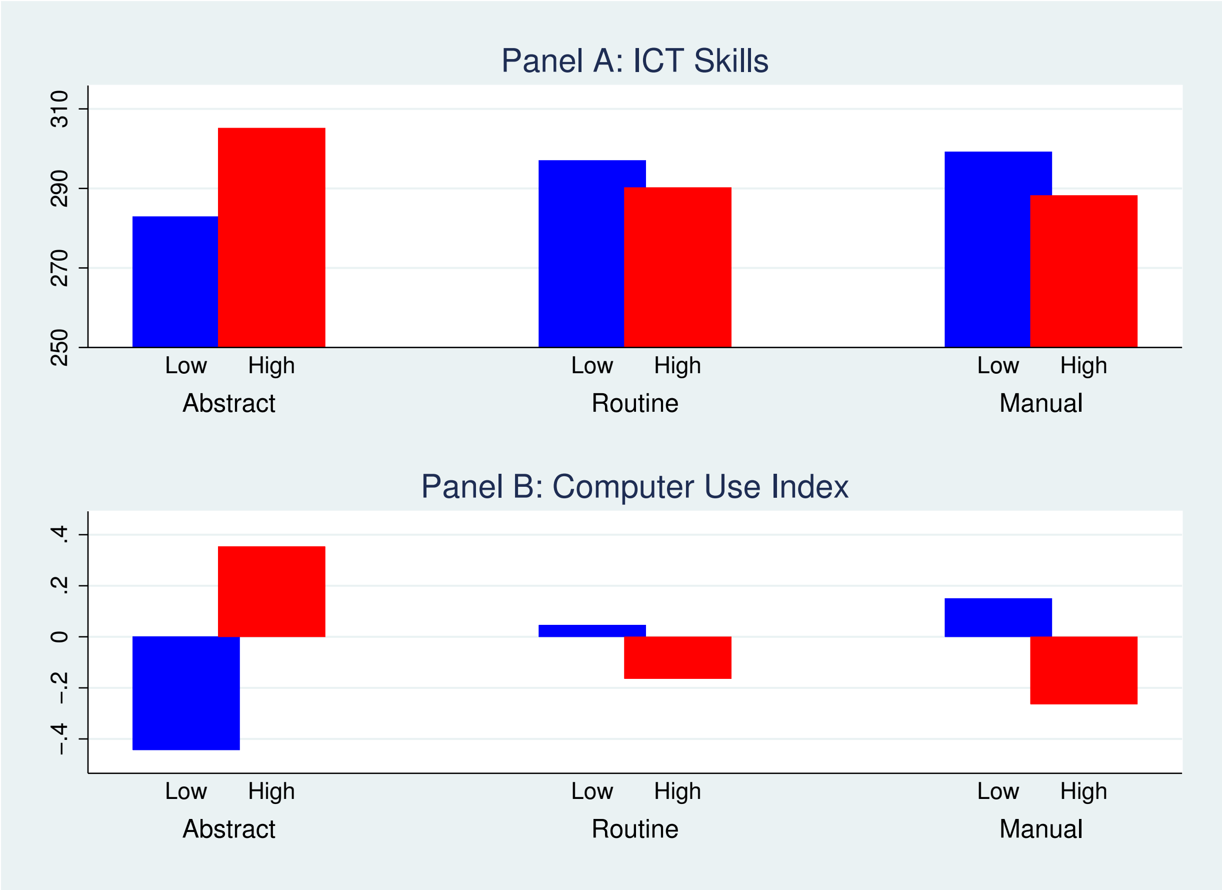
Notes: Coefficient estimates on fixed-line diffusion (in 1996) for indicated five-year age groups in a regression of ICT skills (standardized to std. dev. 1 across countries) on fixed-line diffusion and all control variables included in Table 2, Column (6). Sample: employees, no first-generation migrants. Slopes of solid lines reflect average change in the effect of fixed-line diffusion on ICT skills by age groups (separately estimated for ages 20-49 and 50-65). *Data sources:* ITU, OECD, PIAAC.

Figure 4: Preexisting Fixed-Line Diffusion and ICT Skills (First Stage)



Notes: Added-variable plot from a regression of ICT skills on fixed-line diffusion (in 1996) and all control variables included in Table 2, Column (6). Sample: employees aged 20–49, no first-generation migrants. Based on individual-level regressions that are then aggregated to the country level. Solid line is fitted through all country-level observations; in fitting the dashed line, Ireland and Sweden were excluded. *Data sources:* ITU, OECD, PIAAC.

Figure 5: ICT Skills and Computer Use by Occupational Task Content



Notes: Sample: employees aged 20–49, no first-generation migrants; 222 individuals who did not provide information on their occupation are also excluded. To distinguish between "high" and "low" task intensities, we use the population median in abstract, routine, and manual tasks, respectively. Task measures are taken from Goos, Manning, and Salomons (2014) and are defined at the two-digit ISCO level. 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, Liebman, and Katz (2007) and then aggregated to the country-occupation (two-digit ISCO level) level. *Data sources:* Goos, Manning, and Salomons (2014), PIAAC.

Table 1: Preexisting Fixed-Line Diffusion and ICT Skills by Migration Status

Dependent variable: ICT skills	Natives	2nd-gen. migrants	1st-gen. migrants
Fixed-line diffusion in 1996	11.997***	9.616***	–1.343
	(1.674)	(1.430)	(1.521)
GDP per capita in 1996 (log)	1.154*	0.959*	1.110
	(0.613)	(0.535)	(1.170)
Average wage level 50_59 (log)	–3.137***	–2.239***	–2.431**
	(0.729)	(0.625)	(1.110)
Experience	–0.073**	–0.066	–0.054
	(0.027)	(0.040)	(0.057)
Experience^2 (/100)	–0.111	0.002	0.059
	(0.077)	(0.124)	(0.151)
Female	–0.954***	–0.717***	–0.887***
	(0.104)	(0.172)	(0.200)
Years of schooling	0.672***	0.711***	0.692***
	(0.027)	(0.030)	(0.048)
R squared (adjusted)	0.18	0.18	0.14
Individuals	36,667	4,014	4,842
Countries	19	19	19

Notes: Ordinary least squares estimation weighted by sampling weights (giving same weight to each country). Sample: employees aged 20–49. ICT skills are standardized to std. dev. 1 across countries, using the country-level std. dev. as "numeraire" scale. *Native:* participant and both parents born in the country of residence. *1st-gen. migrants:* participant born abroad; at least one parent as well. *2nd-gen. migrants:* mother, father, or both born abroad; participant born in country of residence. *Fixed-line diffusion in 1996:* voice-telephony penetration rate (telephone access lines per inhabitant) in 1996. *GDP per capita in 1996 (log)* is measured in PPP-US-$ and obtained from the OECD. *Average wage level 50_59 (log)* is the mean wage (in purchasing power parities) of employees aged 50–59, without first-generation migrants, obtained from PIAAC. Fixed-line diffusion, GDP per capita, and average wages of exit-age workers are measured at the country level; all other variables are measured at the individual level. Robust standard errors, adjusted for clustering at the country level, in parentheses. Significance levels: * p<0.10, ** p<0.05, *** p<0.01. *Data sources:* ITU, OECD, PIAAC.

Table 2: Returns to ICT Skills: Cross-Country Baseline Estimates

Dependent variable: log gross hourly wage						
	OLS			IV (Second Stage)		
	(1)	(2)	(3)	(4)	(5)	(6)
ICT skills	0.096***	0.120***	0.073***	0.059**	0.053**	0.075***
	(0.009)	(0.008)	(0.009)	(0.026)	(0.023)	(0.012)
GDP per capita in 1996 (log)	–0.062	–0.158	–0.104	–0.125	–0.217*	–0.247**
	(0.119)	(0.099)	(0.120)	(0.132)	(0.117)	(0.114)
Average wage level 50_59 (log)	0.866***	0.904***	0.841***	0.865***	0.906***	0.885***
	(0.106)	(0.085)	(0.106)	(0.112)	(0.087)	(0.093)
Experience		0.043***	0.037***		0.043***	0.042***
		(0.003)	(0.003)		(0.003)	(0.003)
Experience^2 (/100)		–0.080***	–0.063***		–0.071***	–0.057***
		(0.007)	(0.007)		(0.012)	(0.008)
Female		–0.121***	–0.148***		–0.101***	–0.094***
		(0.018)	(0.018)		(0.018)	(0.016)
Years of schooling			0.057***			0.020**
			(0.005)			(0.009)
First stage (Dependent variable: ICT skills)						
Fixed-line diffusion in 1996				6.183***	6.568***	11.601***
				(1.102)	(0.905)	(1.554)
Instrument F statistic				31.5	52.6	55.7
Individuals	40,869	40,869	40,869	40,869	40,869	40,869
Countries	19	19	19	19	19	19

Notes: Ordinary least squares estimation (Columns (1)–(3)) and two-stage least squares estimation (Columns (4)–(6)) weighted by sampling weights (giving same weight to each country). Sample: employees aged 20–49, no first-generation migrants. Dependent variable, *log gross hourly wage*, is measured in purchasing power parities. ICT skills are standardized to std. dev. 1 across countries; in Columns (4)–(6) with the country-level std. dev. as "numeraire" scale. *Fixed-line diffusion in 1996:* voice-telephony penetration rate (telephone access lines per inhabitant) in 1996. *GDP per capita in 1996 (log)* is measured in PPP-US-$ and obtained from the OECD. *Average wage level 50_59 (log)* is the mean wage (in purchasing power parities) of employees aged 50–59, without first-generation migrants, obtained from PIAAC. Fixed-line diffusion, GDP per capita, and average wages of exit-age workers are measured at the country level; all other variables are measured at the individual level. See Table A-3 for the first-stage results of Columns (4)–(6). Robust standard errors, adjusted for clustering at the country level, in parentheses. Significance levels: * p<0.10, ** p<0.05, *** p<0.01. *Data sources:* ITU, OECD, PIAAC.

Table 3: Cross-Country Placebo Test

Dependent variable: cognitive skills as indicated in column header	No control for other skill			Control for other skill			
	Numeracy	Literacy	ICT	Numeracy	Literacy	ICT	ICT
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Fixed-line diffusion in 1996	8.356***	9.364***	11.601***	1.769	1.984	4.529***	3.697***
	(2.642)	(2.108)	(1.554)	(1.860)	(1.190)	(0.923)	(0.598)
ICT skills				0.568***	0.636***		
				(0.016)	(0.016)		
Numeracy skills						0.846***	
						(0.016)	
Literacy skills							0.844***
							(0.014)
GDP per capita in 1996 (log)	0.799	0.193	1.183*	0.127	–0.560	0.507	1.020***
	(0.861)	(0.839)	(0.584)	(0.578)	(0.555)	(0.310)	(0.354)
Average wage level 50_59 (log)	–2.913**	–2.181**	–3.050***	–1.182	–0.241	–0.584	–1.209***
	(1.223)	(1.001)	(0.699)	(0.852)	(0.610)	(0.406)	(0.310)
Experience	0.045**	0.009	–0.073**	0.087***	0.056***	–0.111***	–0.081***
	(0.018)	(0.020)	(0.025)	(0.012)	(0.011)	(0.017)	(0.015)
Experience^2 (/100)	–0.183***	–0.168***	–0.094	–0.130***	–0.108***	0.061	0.048
	(0.050)	(0.057)	(0.073)	(0.032)	(0.032)	(0.048)	(0.042)
Female	–1.325***	–0.508***	–0.925***	–0.800***	0.081	0.197**	–0.496***
	(0.097)	(0.072)	(0.104)	(0.076)	(0.063)	(0.089)	(0.083)
Years of schooling	0.629***	0.702***	0.677***	0.245***	0.271***	0.145***	0.085***
	(0.030)	(0.032)	(0.026)	(0.019)	(0.017)	(0.018)	(0.017)
R squared (adjusted)	0.18	0.18	0.18	0.57	0.62	0.57	0.62
Individuals	40,869	40,869	40,869	40,869	40,869	40,869	40,869
Countries	19	19	19	19	19	19	19

Notes: Ordinary least squares estimation weighted by sampling weights (giving same weight to each country). Sample: employees aged 20–49, no first-generation migrants. Numeracy, literacy, and ICT skills are standardized to std. dev. 1 across countries, using the country-level std. dev. as "numeraire" scale. *Fixed-line diffusion in 1996:* voice-telephony penetration rate (telephone access lines per inhabitant) in 1996. *GDP per capita in 1996 (log)* is measured in PPP-US-$ and obtained from the OECD. *Average wage level 50_59 (log)* is the mean wage (in purchasing power parities) of employees aged 50–59, without first-generation migrants, obtained from PIAAC. Fixed-line diffusion, GDP per capita, and average wages of exit-age workers are measured at the country level; all other variables are measured at the individual level. Robust standard errors, adjusted for clustering at the country level, in parentheses. Significance levels: * p<0.10, ** p<0.05, *** p<0.01. *Data sources:* ITU, OECD, PIAAC.

Table 4: Returns to ICT Skills: Robustness

Second stage (Dependent variable: log gross hourly wage)									
	Further country controls								No post-com.
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
ICT skills	0.081***	0.058***	0.077***	0.050***	0.077***	0.073***	0.071***	0.069***	0.082***
	(0.013)	(0.014)	(0.011)	(0.012)	(0.011)	(0.013)	(0.012)	(0.013)	(0.021)
Service share	–0.339								
	(0.353)								
Union density		0.217***							
		(0.081)							
Employment protection			0.011						
			(0.022)						
Public sector				0.774***					
				(0.220)					
Youth unemployment rate					0.302				
					(0.248)				
People in tertiary education						1.459			
						(2.656)			
Cable diffusion in 1996							0.140		
							(0.130)		
Mobile diffusion in 2012								0.001*	
								(0.001)	
Country characteristics	X	X	X	X	X	X	X	X	X
Individual characteristics	X	X	X	X	X	X	X	X	X
First stage (Dependent variable: ICT skills)									
Fixed-line diffusion in 1996	11.063***	10.286***	12.536***	11.332***	11.486***	12.087***	11.371***	10.608***	9.986***
	(1.595)	(1.852)	(1.389)	(1.893)	(1.493)	(1.657)	(1.683)	(1.433)	(1.902)
Instrument F statistic	48.1	30.8	81.4	35.8	59.2	53.2	45.6	54.8	27.6
Individuals	40,869	40,869	40,869	40,869	40,869	40,869	40,869	40,869	33,391
Countries	19	19	19	19	19	19	19	19	15

Notes: Two-stage least squares estimation weighted by sampling weights (giving same weight to each country). Sample: employees aged 20–49, no first-generation migrants. Column (9) is without post-communist countries (i.e., Czech Rep., Estonia, Poland, Slovak Rep.). Dependent variable in second stage, *log gross hourly wage*, is measured in purchasing power parities. ICT skills are standardized to std. dev. 1 across countries, using the country-level std. dev. as "numeraire" scale. *Fixed-line diffusion in 1996:* voice-telephony penetration rate (telephone access lines per inhabitant) in 1996. *Service sector:* share of service sector in the GDP. *Union density:* share of wage and salary earners who are trade union members. *Employment protection:* employment protection legislation (EPL), composite indicator measuring strength of employment protection for individual and collective dismissals. *Public sector:* share of workers employed in the public sector. *Youth unemployment rate:* unemployment rate of persons aged 15–24. *Enrollment tertiary education:* share of population currently in tertiary education. *Cable diffusion in 1996:* cable television subscribers per 100 inhabitants in 1996. *Mobile diffusion in 2012:* mobile-cellular telephone subscriptions per 100 inhabitants in 2012. Country characteristics are GDP per capita in 1996 (in logs) and average wages of exit-age workers in 2011/2012 (in logs). Individual characteristics are quadratic polynomial in work experience, gender, and years of schooling. All variables except for ICT skills and individual characteristics are measured at the country level. See Table 1 for details. Robust standard errors, adjusted for clustering at the country level, in parentheses. Significance levels: * p<0.10, ** p<0.05, *** p<0.01. *Data sources:* ITU, OECD, PIAAC, Statistics Canada, UNESCO Institute for Statistics.

Table 5: Returns to ICT Skills: Adding Individual-Level Controls

Second stage (Dependent variable: log gross hourly wage)								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
ICT skills	0.070***	0.068***	0.076***	0.079***	0.075***	0.073***	0.066***	0.075***
	(0.015)	(0.015)	(0.012)	(0.013)	(0.010)	(0.012)	(0.013)	(0.012)
Age	0.058***							
	(0.008)							
Age^2 (/100)	–0.050***							
	(0.012)							
Potential work experience		0.040***						
		(0.003)						
Potential work experience^2 (/100)		–0.054***						
		(0.009)						
Full-time			–0.017					
			(0.046)					
Parental education				–0.031***				
				(0.011)				
Health					0.025***			
					(0.009)			
Country characteristics	X	X	X	X	X	X	X	X
Individual characteristics	X	X	X	X	X	X	X	X
Firm size						X		
Occupation fixed effects							X	
Industry fixed effects								X
First stage (Dependent variable: ICT skills)								
Fixed-line diffusion in 1996	11.865***	11.735***	11.588***	10.472***	11.963***	11.419***	10.004***	11.277***
	(1.831)	(1.811)	(1.565)	(1.557)	(1.608)	(1.504)	(1.258)	(1.547)
Instrument F statistic	42.0	42.0	54.9	45.2	55.3	57.6	63.2	53.1
Individuals	40,869	40,869	40,869	39,062	33,334	40,718	40,482	40,373
Countries	19	19	19	19	18	19	19	19

Notes: Two-stage least squares estimation weighted by sampling weights (giving same weight to each country). Sample: employees aged 20–49, no first-generation migrants. Column (5) is without Canada because the health variable is not reported. Dependent variable in second stage, *log gross hourly wage*, is measured in purchasing power parities. ICT skills are normalized with std. dev. 1 across countries, using the country-level std. dev. as "numeraire" scale. *Fixed-line diffusion in 1996:* voice-telephony penetration rate (telephone access lines per inhabitant) in 1996. *Potential experience:* replaces the quadratic polynomial in actual work experience by a quadratic polynomial in potential work experience (age minus years of schooling minus 6). *Full-time:* 1 = working more than 30 hours per week. *Parental education:* 1 = neither parent attained upper secondary education; 2 = at least one parent attained upper secondary education; 3 = at least one parent attained tertiary education. *Health:* 1 = poor; 2 = fair; 3 = good; 4 = very good; 5 = excellent. In Column (6), we control for the number of workers in the PIAAC respondent's firm: 1 = 1–10 employees; 2 = 11–50 employees; 3 = 51 – 250 employees; 4 = 251–1,000 employees; 5 = more than 1,000 employees. In Column (7) (Column (8)), we add controls for one-digit occupation categories (one-digit industry categories). Country characteristics are GDP per capita in 1996 (in logs) and average wages of exit-age workers in 2011/2012 (in logs). Individual characteristics are quadratic polynomial in work experience (not in Columns (1) and (2)), gender, and years of schooling. All variables except for fixed-line diffusion, GDP per capita, and average wages of exit-age workers are measured at the individual level. See Table 1 for details. Robust standard errors, adjusted for clustering at the country level, in parentheses. Significance levels: * p<0.10, ** p<0.05, *** p<0.01. *Data sources:* ITU, OECD, PIAAC.

Table 6: Returns to ICT Skills: Within-Country Baseline Estimates

	Full sample			No own MDF sample		
Second stage (Dependent variable: log gross hourly wage)						
	(1)	(2)	(3)	(4)	(5)	(6)
ICT skills	0.203***	0.201***	0.140*	0.224**	0.237**	0.190*
	(0.075)	(0.066)	(0.084)	(0.095)	(0.095)	(0.113)
Municipality characteristics	X	X	X	X	X	X
Experience and gender		X	X		X	X
Years of schooling			X			X
First stage (Dependent variable: ICT skills)						
Threshold	–0.895***	–0.824***	–0.586***	–1.259***	–1.123***	–0.807**
	(0.268)	(0.258)	(0.222)	(0.322)	(0.335)	(0.321)
Instrument F statistic	11.2	10.2	6.9	15.3	11.3	6.3
Individuals	1,417	1,417	1,417	122	122	122
Municipalities	205	205	205	18	18	18

Notes: Instrumental-variable estimation weighted by sampling weights (giving same weight to each country). Sample: West German employees aged 20–49, no first-generation migrants. Columns (1)–(3) show results for all West German municipalities in the sample; Columns (4)–(6) restrict sample to West German municipalities without an own main distribution frame (MDF). ICT skills are measured at the individual level and are standardized to std. dev. 1, using the municipality-level std. dev. as "numeraire" scale. The instrument is a threshold dummy indicating whether a municipality is more than 4,200 meters away from its main distribution frame (MDF) (1 = lower probability of DSL availability, and 0 otherwise). Distance calculations are based on municipalities' geographic centroid. Estimation is implemented through Limited Information Maximum Likelihood (LIML), where the user-specified constant (alpha) is set to 1. Fuller's (1977) modification of the LIML estimator is used, which ensures that the estimator has finite moments. Municipality characteristics are unemployment rate (i.e., share of unemployed individuals in the working-age population aged 18 to 65), population share of individuals older than 65, and average municipality-level wage of workers aged 50-60 years (obtained from PIAAC). 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 7: Within-Country Placebo Test

		Panel A: Full Sample		
Dependent variable: cognitive skills in				
	Numeracy	Literacy	ICT	ICT
Threshold	0.278**	0.049	–0.502***	–0.310*
	(0.123)	(0.165)	(0.142)	(0.167)
ICT skills	0.676***	0.709***		
	(0.023)	(0.022)		
Numeracy skills			0.709***	
			(0.020)	
Literacy skills				0.754***
				(0.020)
R squared (adjusted)	0.62	0.65	0.59	0.63
Individuals	1,417	1,417	1,417	1,417
Municipalities	205	205	205	205
		Panel B: No Own MDF Sample		
Dependent variable: cognitive skills in				
	Numeracy	Literacy	ICT	ICT
Threshold	0.209	0.164	–0.616***	–0.482***
	(0.149)	(0.149)	(0.211)	(0.139)
ICT skills	0.599***	0.706***		
	(0.060)	(0.067)		
Numeracy skills			0.696***	
			(0.065)	
Literacy skills				0.801***
				(0.066)
R squared (adjusted)	0.62	0.68	0.60	0.70
Individuals	122	122	122	122
Municipalities	18	18	18	18
		Controls in Panels A + B		
Municipality characteristics	X	X	X	X
Individual characteristics	X	X	X	X

Notes: Ordinary least squares estimation weighted by sampling weights. Sample: West German employees aged 20–49, no first-generation migrants. Numeracy, literacy, and ICT skills are measured at the individual level and are standardized to std. dev. 1, using the municipality-level std. dev. as "numeraire" scale. *Threshold:* indicates whether a municipality is more than 4,200 meters away from its main distribution frame (MDF) (1 = lower probability of DSL availability, and 0 otherwise). Municipality characteristics are unemployment rate (i.e., share of unemployed individuals in the working-age population aged 18 to 65), population share of individuals older than 65, and average municipality-level wage of workers aged 50-60 years (obtained from PIAAC). Individual characteristics are quadratic polynomial in work experience, gender, and years of schooling. 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.

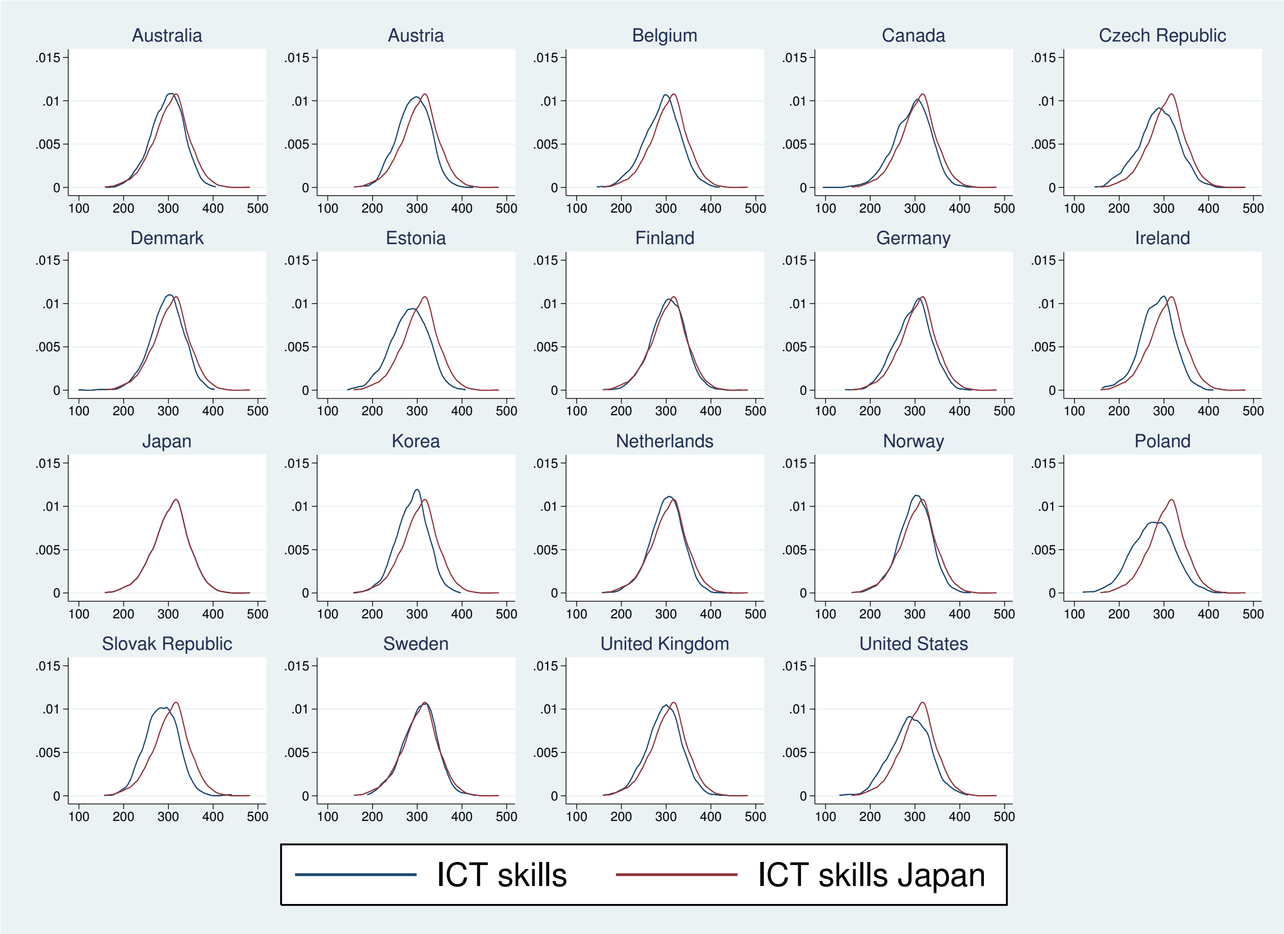
Table 8: Are Returns to ICT Skills Related to Computer Use and Tasks at Work?

Second stage (Dependent variable: log gross hourly wage)						
	(1)	(2)	(3)	(4)	(5)	(6)
ICT skills	0.063***	0.068***	0.063***	0.064***	0.068***	0.063***
	(0.010)	(0.009)	(0.010)	(0.010)	(0.009)	(0.009)
× computer use	–0.012					
	(0.012)					
× abstract task intensity		–0.017**			–0.016**	
		(0.008)			(0.008)	
× routine task intensity			0.009		0.003	
			(0.010)		(0.009)	
× manual task intensity				0.008	0.002	
				(0.014)	(0.014)	
× Routine Task Index (RTI)						0.008
						(0.007)
Computer use	–0.054					
	(0.040)					
Country characteristics	X	X	X	X	X	X
Individual characteristics	X	X	X	X	X	X
Occupation fixed effects	X	X	X	X	X	X
Instrument F statistic main effect	136.9	138.6	138.3	137.0	68.4	137.0
Instrument F statistic interaction	42.9	54.7	54.0	45.2	28.1/28.7/24.8	48.4
Individuals	40,674	40,442	40,442	40,442	40,442	40,442
Country-occupation cells	754	717	717	717	717	717

Notes: Two-stage least squares estimation weighted by sampling weights (giving same weight to each country). Sample: employees aged 20–49, no first-generation migrants; 222 individuals who did not provide information on their occupation are also excluded. Dependent variable in second stage, *log gross hourly wage*, is measured in purchasing power parities. ICT skills are standardized to mean 0 and std. dev. 1 across countries, using the country-level std. dev. as "numeraire" scale. Instruments are *fixed-line diffusion in 1996*, defined as voice-telephony penetration rate (telephone access lines per inhabitant) in 1996, interacted with computer use in Column (1), abstract task intensity in Column (2), routine task intensity in Column (3), manual task intensity in Column (4), all tasks simultaneously in Column (5), and the Routine Task Index (RTI), defined as ln(routine) – ln(abstract) – ln(manual), in Column (6). Computer use intensity is based on questions asking 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 into a single index following the procedure described in Kling, Liebman, and Katz (2007) and then aggregated to the country-occupation (two-digit ISCO level) level. Task measures are taken from Goos, Manning, and Salomons (2014) and are defined at the two-digit ISCO level. All variables are de-meaned. *Instrument F statistic main* refers to instrumentation of ICT skills and *Instrument F statistic interaction* refers to instrumentation of ICT-skills interactions. All specifications include two-digit occupation fixed effects. Main effects of occupational task intensities cannot be estimated because variables do not vary within occupations. Country characteristics are GDP per capita in 1996 (in logs) and average wages of exit-age workers in 2011/2012 (in logs). Controls for individual characteristics include quadratic polynomial in work experience, gender, and years of schooling. Robust standard errors, adjusted for clustering at the country-occupation level, in parentheses. Significance levels: * p<0.10, ** p<0.05, *** p<0.01. *Data sources:* Goos, Manning, and Salomons (2014), ITU, OECD, PIAAC.

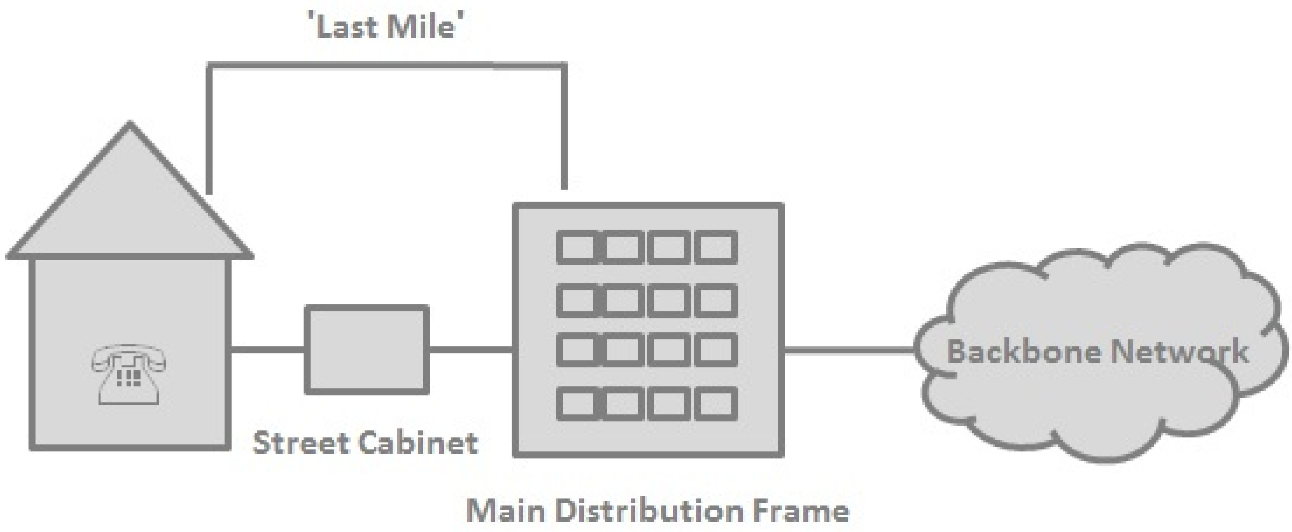
Appendix

Figure A-1: ICT Skills Within Countries



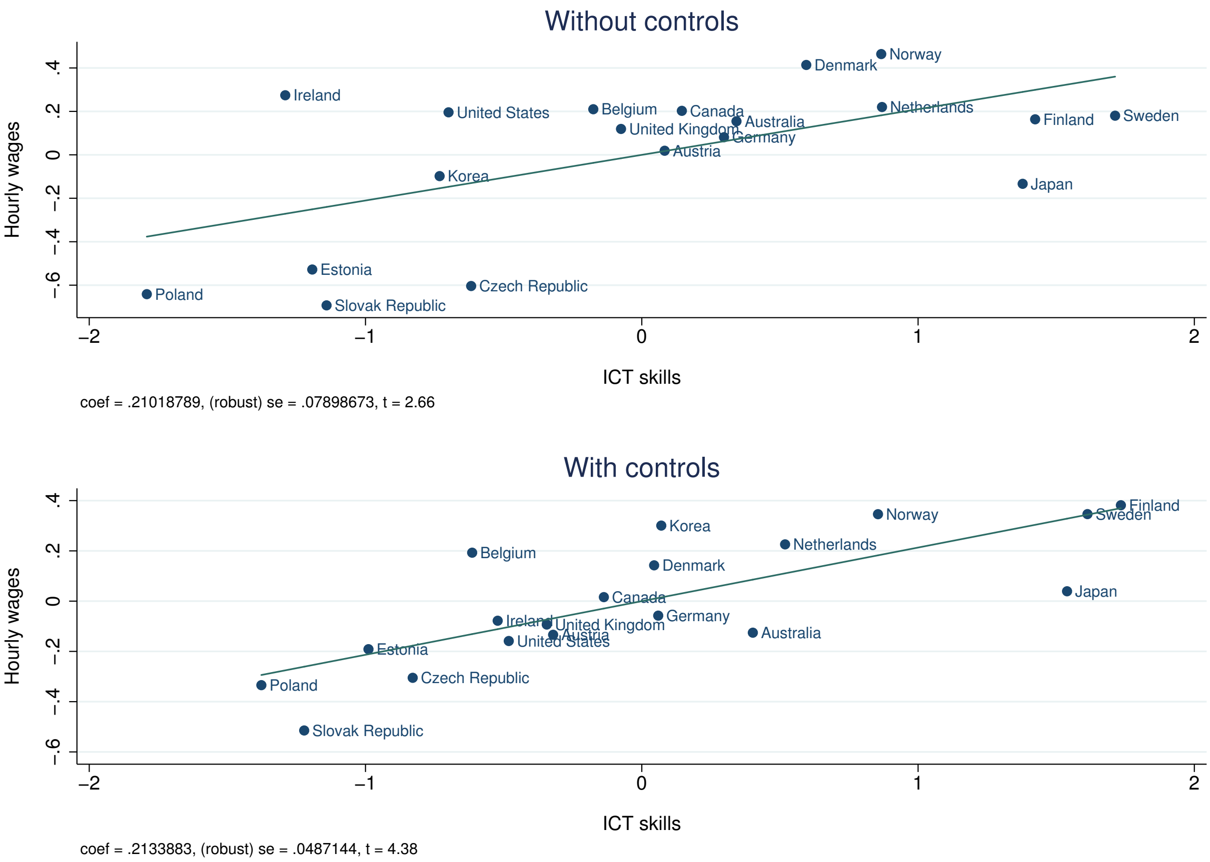
Notes: Smoothed kernel density plots are shown. A kernel density plot of Japan (i.e., the country with highest average ICT skills) is shown in each panel. Sample: employees aged 20–49 (no first-generation migrants). *Data source:* PIAAC.

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 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 Subscriber Line Access Multiplexer) is installed that aggregates and redirects the voice and data traffic to the telcos backbone network.

Figure A-3: Returns to ICT Skills: Country-Level Least Squares Results



Notes: Sample: employees aged 20–49 (no first-generation migrants). All variables are aggregated to the country level. The graph in the top panel does not include any controls. The graph in the bottom panel is an added-variable plot that controls for work experience (linear and squared), gender, and years of schooling. Country-level ICT skills are normalized with std. dev. 1. *Data sources:* ITU, OECD, PIAAC.

Table A-1: Descriptive Statistics (Individual-Level Variables)

	Pooled	Australia	Austria	Belgium	Canada	Czech R.	Denmark	Estonia	Finland	Germany
Gross hourly wage	17.7	18.7	16.3	19.2	19.9	9.1	23.6	10.5	18.4	18.5
(in PPP-US-$)	(9.7)	(8.3)	(6.3)	(6.5)	(9.0)	(4.2)	(8.1)	(6.3)	(6.8)	(9.4)
ICT skills	294.0	297.3	291.4	291.0	293.5	287.2	296.5	282.2	304.3	295.4
	(39.8)	(36.5)	(36.1)	(40.2)	(41.3)	(43.9)	(37.5)	(41.0)	(37.9)	(39.6)
Yrs schooling	13.9	14.9	12.7	13.5	13.7	13.7	13.4	12.8	13.5	14.1
	(2.5)	(2.1)	(2.3)	(2.3)	(2.2)	(2.4)	(2.4)	(2.6)	(2.7)	(2.3)
Experience (years)	14.0	14.6	15.4	14.8	15.4	13.0	16.8	12.2	12.8	14.3
	(8.4)	(8.4)	(8.7)	(8.3)	(8.5)	(7.8)	(8.6)	(7.9)	(8.0)	(9.0)
Female (share)	0.48	0.48	0.50	0.49	0.48	0.44	0.50	0.53	0.50	0.47
Observations	40,869	1,926	1,667	1,764	7,531	1,594	1,902	2,162	2,013	1,906

	Ireland	Japan	Korea	Netherl.	Norway	Poland	Slovak R.	Sweden	U.K.	U.S.
Gross hourly wage	22.2	15.3	17.0	19.9	24.6	9.4	9.0	18.2	18.9	21.1
(in PPP-US-$)	(11.3)	(9.2)	(13.4)	(8.6)	(8.4)	(5.5)	(6.0)	(5.3)	(11.4)	(12.7)
ICT skills	284.7	305.6	288.5	300.8	299.8	276.0	284.8	305.3	295.2	289.2
	(37.6)	(40.9)	(34.9)	(36.5)	(36.2)	(47.0)	(36.8)	(37.7)	(39.3)	(43.3)
Yrs schooling	16.2	13.8	14.3	14.0	14.8	14.5	14.2	12.8	13.3	14.2
	(2.3)	(2.3)	(2.3)	(2.2)	(2.2)	(2.6)	(2.5)	(2.2)	(2.3)	(2.5)
Experience (years)	14.0	13.5	9.8	14.6	14.6	10.4	12.8	13.7	15.7	15.5
	(8.0)	(7.8)	(6.9)	(8.0)	(8.1)	(7.7)	(8.3)	(8.7)	(8.8)	(8.6)
Female (share)	0.56	0.41	0.44	0.49	0.49	0.47	0.48	0.49	0.48	0.52
Observations	1,451	1,677	1,934	1,854	1,980	2,365	1,357	1,595	2,818	1,373

Notes: Means, standard deviations (in parentheses), and number of observations for selected variables by country. Sample: employees aged 20–49, no first-generation migrants. Pooled specification gives same weight to each country. *Data source:* PIAAC.

Table A-2: Descriptive Statistics (Country-Level Variables)

	Pooled	Australia	Austria	Belgium	Canada	Czech R.	Denmark	Estonia	Finland	Germany
First emergence of broadband		1999	1999	2000	1999	2000	1999	2000	1999	1999
Fixed-line diffusion in 1996	0.49	0.50	0.48	0.46	0.61	0.27	0.62	0.31	0.55	0.54
GDP per capita in 1996 (/1000)	25.05	28.37	29.06	27.50	28.90	17.37	29.12	8.47	22.61	27.95
Average wage level 50_59	18.80	20.67	17.58	22.12	21.90	8.56	24.93	8.21	19.00	19.68
Service sector	0.70	0.69	0.70	0.77	0.70	0.60	0.77	0.67	0.71	0.69
Union density	0.32	0.18	0.28	0.50	0.27	0.17	0.69	0.08	0.69	0.18
Employment protection	2.30	1.99	2.44	3.08	1.51	2.75	2.32	2.07	2.17	2.98
Public sector	0.29	0.25	0.26	0.29	0.33	0.26	0.39	0.30	0.36	0.15
Youth unemployment rate	0.16	0.12	0.09	0.20	0.14	0.19	0.14	0.20	0.18	0.08
Enrollment tertiary education	0.05	0.06	0.04	0.04	0.04	0.04	0.05	0.05	0.06	0.04
Cable diffusion in 1996	0.19	0.02	0.10	0.36	0.27	0.06	0.24	0.44	0.16	0.20
Mobile diffusion in 2012	122.61	105.59	160.54	111.33	80.05	126.85	117.57	160.41	172.32	111.59
	Ireland	Japan	Korea	Netherl.	Norway	Poland	Slovak R.	Sweden	U.K.	U.S.
First emergence of broadband	2000	1999	2000	1999	1999	2001	2000	1999	1999	1999
Fixed-line diffusion in 1996	0.38	0.51	0.43	0.54	0.57	0.17	0.23	0.68	0.53	0.62
GDP per capita in 1996	23.55	28.69	16.92	29.31	39.54	9.64	11.55	25.00	25.68	36.02
Average wage level 50_59	23.39	18.76	18.19	22.43	26.12	8.87	8.08	18.80	18.65	24.38
Service sector	0.71	0.71	0.58	0.74	0.57	0.63	0.62	0.73	0.79	0.80
Union density	0.33	0.18	0.10	0.18	0.55	0.15	0.17	0.67	0.26	0.11
Employment protection	1.98	2.09	2.17	2.88	2.31	2.39	2.63	2.52	1.71	1.17
Public sector	0.32	0.13	0.16	0.29	0.38	0.22	0.28	0.39	0.34	0.23
Youth unemployment rate	0.33	0.08	0.09	0.09	0.09	0.26	0.34	0.24	0.21	0.16
Enrollment tertiary education	0.04	0.03	0.07	0.05	0.05	0.05	0.04	0.05	0.04	0.07
Cable diffusion in 1996	0.15	0.10	0.15	0.37	0.15	0.07	0.08	0.21	0.04	0.24
Mobile diffusion in 2012	107.21	110.91	109.43	117.97	116.68	140.34	111.91	124.57	135.29	95.45

Notes: Only country-level characteristics reported. *First emergence of broadband:* year in which predicted broadband penetration reaches 1 percent. *Fixed-line diffusion in 1996:* voice-telephony penetration rate (telephone access lines per inhabitant) in 1996. *GDP per capita in 1996* is measured in PPP-US-$. *Average wage level 50_59* is the mean wage (in purchasing power parities) of employees aged 50–59, without first-generation migrants, in PIAAC. *Service sector:* share of service sector in the GDP. *Union density:* share of wage and salary earners who are trade union members. *Employment protection:* employment protection legislation (EPL), composite indicator measuring strength of employment protection for individual and collective dismissals. *Public sector:* share of workers employed in the public sector. *Youth unemployment rate:* unemployment rate of persons aged 15–24. *Enrollment tertiary education:* share of population currently in tertiary education. *Cable diffusion in 1996:* cable television subscribers per 100 inhabitants in 1996. *Mobile diffusion in 2012:* mobile-cellular telephone subscriptions per 100 inhabitants in 2012. GDP per capita is expressed in PPP-US-$ (divided by 1,000). Pooled specification gives same weight to each country. *Data sources:* ITU, OECD, PIAAC, Statistics Canada, UNESCO Institute for Statistics.

Table A-3: Returns to ICT Skills: Instrumental-Variables Estimates (First Stage)

Dependent variable: ICT skills			
	(1)	(2)	(3)
Fixed-line diffusion in 1996	6.183***	6.568***	11.601***
	(1.102)	(0.905)	(1.554)
GDP per capita in 1996 (log)	0.900	1.269**	1.183*
	(0.574)	(0.517)	(0.584)
Average wage level 50_59 (log)	–1.156**	–1.319***	–3.050***
	(0.413)	(0.427)	(0.699)
Experience		–0.014	–0.073**
		(0.027)	(0.025)
Experience^2 (/100)		–0.328***	–0.094
		(0.080)	(0.073)
Female		–0.672***	–0.925***
		(0.134)	(0.104)
Years of schooling			0.677***
			(0.026)
Instrument F statistic	31.5	52.6	55.7
Individuals	40,869	40,869	40,869
Countries	19	19	19

Notes: Table reports first-stage results of two-stage least squares estimations presented in Table 2, Columns (4)–(6). Robust standard errors, adjusted for clustering at the country level, in parentheses. Significance levels: * p<0.10, ** p<0.05, *** p<0.01. *Data sources:* ITU, OECD, PIAAC.

Table A-4: Returns to ICT Skills: Cross-Country Simultaneous-Equations Estimation

Third stage (Dependent variable: log gross hourly wage)			
	(1)	(2)	(3)
ICT skills	0.059**	0.053**	0.075***
	(0.027)	(0.024)	(0.012)
Country characteristics	X	X	X
Experience and gender		X	X
Years of schooling			X
Second stage (Dependent variable: ICT skills)			
Broadband diffusion in 2012	21.552*	22.884*	41.835**
	(12.085)	(12.444)	(19.276)
First stage (Dependent variable: broadband diffusion in 2012)			
Fixed-line diffusion in 1996	0.287*	0.287*	0.277*
	(0.148)	(0.148)	(0.144)
Individuals	40,869	40,869	40,869
Countries	19	19	19

Notes: Three-equation seemingly unrelated regression estimation weighted by sampling weights (giving same weight to each country). Sample: employees aged 20–49, no first-generation migrants. Dependent variable in third stage, *log gross hourly wage*, is measured in purchasing power parities. ICT skills are standardized to std. dev. 1 across countries, using the country-level std. dev. as “numeraire” scale. *Broadband diffusion in 2012:* actual diffusion of broadband Internet (number of broadband subscribers per inhabitant) in 2012 (see Figure 2). *Fixed-line diffusion in 1996:* voice-telephony penetration rate (telephone access lines per inhabitant) in 1996. Broadband diffusion, fixed-line diffusion, GDP per capita, and average wages of exit-age workers are measured at the country level; all remaining variables are measured at the individual level. See Table 1 for details on the control variables. Robust standard errors, adjusted for clustering at the country level, in parentheses. Significance levels: * $p<0.10$, ** $p<0.05$, *** $p<0.01$. *Data sources:* ITU, OECD, PIAAC.

Table A-5: Returns to ICT Skills: Within-Country Simultaneous-Equations Estimation

	Full sample			No own MDF sample		
Third stage (Dependent variable: log gross hourly wage)						
ICT skills	0.213***	0.211***	0.156	0.240**	0.256**	0.224
	(0.082)	(0.072)	(0.095)	(0.108)	(0.110)	(0.145)
Municipality characteristics	X	X	X	X	X	X
Experience and gender		X	X		X	X
Years of schooling			X			X
Second stage (Dependent variable: ICT skills)						
Broadband availability	15.547**	14.213**	10.323**	29.027*	25.306*	19.529
	(6.747)	(5.755)	(5.072)	(15.289)	(13.225)	(12.047)
First stage (Dependent variable: broadband availability)						
Threshold	–0.058***	–0.058***	–0.057***	–0.043**	–0.044**	–0.041*
	(0.020)	(0.020)	(0.020)	(0.021)	(0.022)	(0.022)
Individuals	1,417	1,417	1,417	122	122	122
Municipalities	205	205	205	18	18	18

Notes: Three-equation seemingly unrelated regression estimation weighted by sampling weights. Sample: West German employees aged 20–49, no first-generation migrants. Columns (1)–(3) show results for all West German municipalities in the sample; Columns (4)–(6) restrict sample to West German municipalities without an own main distribution frame (MDF). ICT skills are measured at the individual level and are standardized to std. dev. 1, using the municipality-level std. dev. as "numeraire" scale. *Broadband availability:* share of households in a municipality for which broadband Internet is technologically available (measured in 2008). *Threshold:* indicates whether a municipality is more than 4,200 meters away from its MDF (1 = lower probability of DSL availability, and 0 otherwise). Municipality characteristics are unemployment rate (i.e., share of unemployed individuals in the working-age population aged 18 to 65), population share of individuals older than 65, and average municipality-level wage of workers aged 50-60 years (obtained from PIAAC). Robust standard errors, adjusted for clustering at 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: Are Returns to ICT Skills Related to Computer Use and Tasks at Work? (Country and Occupation FE)

Second stage (Dependent variable: log gross hourly wage)	(1)	(2)	(3)	(4)	(5)	(6)
ICT skills × computer use	–0.022**					
	(0.010)					
ICT skills × abstract task intensity		–0.019**			–0.019**	
		(0.008)			(0.008)	
ICT skills × routine task intensity			0.007		0.001	
			(0.009)		(0.008)	
ICT skills × manual task intensity				0.002	–0.005	
				(0.012)	(0.011)	
ICT skills × Routine Task Index (RTI)						0.011*
						(0.006)
Computer use	0.047*					
	(0.026)					
Individual characteristics	X	X	X	X	X	X
Country fixed effects	X	X	X	X	X	X
Occupation fixed effects	X	X	X	X	X	X
Instrument F statistic interaction	93.6	123.9	101.7	58.2	42.2/34.6/24.3	88.8
Individuals	40,674	40,442	40,442	40,442	40,442	40,442
Country-occupation cells	754	717	717	717	717	717

Notes: Two-stage least squares estimation weighted by sampling weights (giving same weight to each country). Sample: employees aged 20–49, no first-generation migrants; 222 individuals who did not provide information on their occupation are also excluded. Dependent variable in second stage, *log gross hourly wage*, is measured in purchasing power parities. ICT skills are standardized to mean 0 and std. dev. 1 across countries, using the country-level std. dev. as "numeraire" scale. Instruments are *fixed-line diffusion in 1996*, defined as voice-telephony penetration rate (telephone access lines per inhabitant) in 1996, interacted with computer use in Column (1), abstract task intensity in Column (2), routine task intensity in Column (3), manual task intensity in Column (4), all tasks simultaneously in Column (5), and with the Routine Task Index (RTI), defined as ln(routine) – ln(abstract) – ln(manual), in Column (6). Computer use intensity is based on questions asking 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, Liebman, and Katz (2007) and then aggregated into the country-occupation (two-digit ISCO level) level. Task measures are taken from Goos, Manning, and Salomons (2014) and are defined at the two-digit ISCO level. All variables are de-meaned. *Instrument F statistic interaction* refers to instrumentation of ICT-skills interactions. All specifications include country and two-digit occupation fixed effects. Main effect of ICT skills cannot be estimated because the instrument, *fixed-line diffusion in 1996*, does not vary within countries; main effects of occupational task intensities cannot be estimated because variables do not vary within occupations. Controls for individual characteristics include quadratic polynomial in work experience, gender, and years of schooling. Robust standard errors, adjusted for clustering at the country-occupation level, in parentheses. Significance levels: * $p<0.10$, ** $p<0.05$, *** $p<0.01$. *Data sources:* Goos, Manning, and Salomons (2014), ITU, OECD, PIAAC.