Returns to ICT Skills*

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Abstract

How important is mastering information and communication technologies (ICT) in modern labor markets? We present the first evidence on this question, drawing 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.

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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 technologies (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 the labor market rewards ICT skills 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 skills is just a reflection of his or her general ability. Using novel, internationally comparable data on individuals' skills in ICT and other domains across 19 countries from the Programme for the International Assessment of Adult Competencies (PIAAC), this paper is the first to investigate the wage returns to ICT skills.

Our identification strategy is based on the idea that ICT skills are developed by performing ICT-related tasks, for which Internet availability is a precondition.[2] We thus estimate instrumental-variable models that exploit exogenous variation in the probability of having Internet access either across or within countries. In the cross-country model, this variation stems from international differences in the rollout of preexisting voice-telephony networks determining the timing of introduction and diffusion speed of broadband Internet in a country. These networks only affect the supply side of broadband diffusion and therefore rule out demand-side effects based on differences in wealth and policy-induced effects (Czernich, Falck, Kretschmer, and Woessmann, 2011). In the within-country model, we exploit technological peculiarities which induced variation in broadband availability at a very fine regional level within Germany. Specifically, 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

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[1] http://www.getonlineweek.eu/vice-president-neelie-kroes-says-digital-literacy-and-e-skills-are-the-new-literacy/; accessed October 27, 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.

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).[3]

We find that both the preexisting voice-telephony infrastructure and the technical threshold are significantly related to individuals' ICT skills, supporting the assertion that a higher technologically determined probability of having Internet access increases the chance and duration of accumulating ICT skills through learning by doing. A series of validity checks add further confidence in our instrumental-variable strategy. For instance, in the cross-country model the extent of a country's traditional voice-telephony network does not predict ICT skills of first-generation immigrants who are unlikely to have acquired ICT skills in the PIAAC test country. Moreover, the instrument is unrelated to a number of variables reflecting a country's economic situation and technological performance before the first emergence of broadband Internet that may also affect wages today. In the within-country model, we show that households without broadband Internet access do not selectively relocate to regions where broadband is available.

Drawing only on variation in ICT skills attributable to exogenously determined broadband access, both instrumental-variable models indicate a positive effect of ICT skills on wages that is economically and statistically significant. In the cross-country analysis, an increase in ICT skills by one standard deviation leads to a 7.5 percent increase in employee wages. In Germany, estimated returns to ICT skills are even larger at 14 percent. These estimates control for a rich set of individual-level variables, including a person's acquired level of schooling, and also account for potential direct effects of broadband diffusion on wages. Moreover, we show in a placebo test that preexisting fixed-line diffusion (across countries) or the technical threshold (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

[3] Other studies have used variation in technological 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 and not based on the decisions of profit-maximizing telecommunication carriers.

general ability) on wages.[5] 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-specific 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 behind the positive returns to ICT skills, namely, that the proliferation of personal computers caused a shift away from routine tasks—that is, those more amenable to automatization—toward problem-solving and complex communication tasks (typically called "nonroutine abstract tasks"). This argument was first made by Autor, Levy, and Murnane (2003) when developing their task-based approach to skill-biased technological change.[6] We observe 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, supporting the main idea of the task-based approach. 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 intensive 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. The complementarity of computers (using and reinforcing ICT skills) and abstract tasks allows workers possessing high ICT skills to benefit from the wage premia paid in abstract jobs.[7]

Previous literature on the returns to computer skills in the labor market highlights the empirical challenges of attempting to estimate causal effects.[8] For example, an influential paper by DiNardo and Pischke (1997) suggests that computer users possess unobserved skills that might have little to

[5] Our result that fixed-line diffusion affects only a specific set of skills is in line with Malamud and Pop-Eleches (2011), who show that home computer ownership has zero or even negative effects on student achievement in math and reading but supports the development of ICT-related skills.

[6] 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), Akerman, Gaardner, and Mogstad (2015), and related earlier work by Acemoglu (1998) and Bresnahan, Brynjolfsson, and Hitt (2002). 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).

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

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

do with computers per se but that increase their productivity. They strikingly demonstrate this by showing that positive wage effects can also be found for pencil use at work that are similar in magnitude to those of computer use. Based on this nonsensical finding, they conclude that returns to computer use at work must be biased due to unobserved skills of the users. Our paper is the first to use a direct measure of ICT skills and estimate its impact on wages. Since we also have information on worker skills in other domains, we can rigorously address DiNardo and Pischke's concern that observed wage differentials between workers with high versus low ICT skills are largely a reflection of unobserved worker heterogeneity.

Our paper also adds to the recently emerging stream of literature that regards direct measures of cognitive skills as more reliable proxies for effective human capital than years of schooling (e.g., Hanushek and Kimko, 2000; Hanushek and Woessmann, 2008). However, the existing literature offers limited 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.[9] 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 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 strategy exploits exogenous variation both across and within countries.

Finally, our paper is also relevant for the burgeoning 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 shows 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). Our results suggest that building ICT skills

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

through e-learning (e.g., Malamud and Pop-Eleches, 2011), even if e-learning itself is not associated with better school grades, might prove beneficial for students' future labor-market outcomes.

The paper is organized as follows. Section 2 describes the PIAAC data and the measurement of ICT skills. Section 3 outlines our instrumental-variable strategy. Section 4 presents the results on the returns to ICT skills from the cross-country analysis, including placebo tests and robustness checks. Section 5 provides the corresponding within-country evidence. Section 6 discusses the relationship between the task content of occupations and ICT skills. Section 7 concludes and derives some implications for policy-making.

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 Assessment of Adult Competencies (PIAAC). PIAAC is the product of collaboration between participating countries through the Organization for Economic Co-operation and Development (OECD), and made use of leading international expertise to develop valid comparisons of skills across countries and cultures. The survey was conducted between August 2011 and March 2012 in 24 countries, which together represent about 75 percent of worldwide GDP.[10] PIAAC was designed to provide representative measures of 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.

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

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.[11] 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.[12]

We focus on ICT skills, defined as "using digital technology, communication tools and networks to acquire and evaluate information, communicate with others and perform practical tasks" (OECD, 2013, p. 86).[13] 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.[14] 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 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,

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11 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.

12 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.

13 *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.

14 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.

which assessed 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. Moreover, 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.[15]

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.[16] 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.[17] 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 40,869 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

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[15] 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).

[16] 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 skills using questions for assessing numeracy skills. For this end we regress ICT skills on numeracy 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 test scores for persons whose scores were initially missing.

[17] 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.

an individual-level standard deviation.[18] The low level of ICT skills in Estonia may appear 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 international average for this age group. The age pattern in ICT skills is even more distinct for the Korean population, which also 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 year olds fall substantially short of international performance and, together with Estonia and Poland, are at the bottom of the international league tables.[19] 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.[20]

<< 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 1,357 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-

[18] 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.

[19] 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.

[20] In the cross-country (within-country) IV strategy we use the country-level (German-municipality-level) standard deviation to standardize ICT skills 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.

USD) across countries.[21] 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.

3. Estimation Strategy

3.1 Empirical Model

We estimate returns to ICT skills in a general Mincer framework (Mincer 1970, 1974) that relates a person's human capital to earnings 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 standard deviation.[22]

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

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[21] 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.

[22] 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).

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.[23] 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 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 priori not clear.

To solve these endogeneity problems, we apply an instrumental-variable (IV) strategy. The basic idea behind our strategy is that individuals acquire ICT skills through learning by doing, and that this learning is facilitated when access to broadband Internet is technically available in a country or region.[24] Specifically, we exploit technologically determined variation in the availability of broadband Internet access via DSL across countries and between highly disaggregated regions within a single country, respectively.

3.2 Characteristics of the DSL Network

DSL, one of the two dominant fixed-line broadband Internet access technologies worldwide, relies on the copper wires of the voice-telephony network connecting households with the main distribution frame (MDF). While these copper wires were used for making fixed-line voice calls before the emergence of the DSL technology, they could be upgraded to provide DSL by installing a

[23] 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.

[24] Before the introduction of broadband Internet, 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. The bandwidth substantially increased with the emergence of broadband, reducing limitations to Internet use as well as excessive waiting times for loading webpages. We thus expect that particularly broadband Internet induces learning-by-doing effects in the accumulation of ICT skills.

new hardware (so called DSLAMs) at the MDFs making data traffic at high bandwidths to the telecommunication carrier's backbone network feasible (see Figure 2). This technological feature of the DSL technology made broadband rollout substantially cheaper as compared to a situation in which new wires (e.g., fiber) would have to be rolled out to the households. Even in countries where fiber was rolled out to the curbs or homes, the existing ducts of traditional fixed-line networks were used to reduce deployment cost of broadband. Thus, the existing fixed-line infrastructure initially built for purposes other than the provision of broadband allowed for an economically viable widespread diffusion of broadband Internet. In consequence, countries with a high fixed-line penetration before the introduction of DSL could roll out broadband at a faster rate (and, in fact, often started the rollout earlier) than countries lagging behind in fixed-line infrastructure.

<< Figure 2 about here >>

At the same time, however, the reliance of broadband rollout on traditional voice-telephony networks also led to an uneven distribution of broadband Internet access within countries. While the distance between the household and the MDF, the so called "last mile", was irrelevant for the quality of voice-telephony services, it determines the maximum bandwidth and therefore plays a crucial role for access to broadband. Above a certain last-mile distance, DSL is no longer feasible without major infrastructure investment. This technological peculiarity of the DSL technology induces exogenous variation in broadband access at a very fine regional level.

It is important to note that variation in broadband availability across or within countries stemming from the technological features described above was especially pronounced in the initial phase of extensive broadband diffusion in the early 2000s. Over time, initial differences in broadband availability 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.

3.3 Cross-Country Instrumental-Variable Model

In our cross-country IV specification, we exploit the extent of the traditional voice-telephony network as a source of exogenous variation in the availability of broadband Internet. Following the reasoning in Section 3.2, we argue that individuals living in countries with a farther-reaching voice-telephony network in 1996 (i.e., before the introduction of broadband Internet in any country[25]) had, on average, earlier access to broadband Internet in any consecutive year, 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). To show that the traditional voice-telephony infrastructure indeed determines broadband rollout in a country, we follow Czernich, Falck, Kretschmer, and Woessmann (2011) and 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 voice-telephony network in 1996, 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 3 plots the actual and estimated broadband Internet diffusion curves across the 19 countries in our sample. To construct the figure, we used data from the OECD Broadband Statistics in combination with ITU data providing the number of broadband subscribers per inhabitant in the

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[25] Broadband was first introduced in Canada in 1997. See also Table A-2.

period 1996 to 2012 and ITU data for the number of telephone access lines per inhabitant, that is, the voice-telephony penetration rate, in 1996.[26] The figure reveals that the estimated broadband Internet diffusion based on Equations (2) and (3) is generally very close to the actual diffusion. Thus, the extent of the preexisting voice-telephony network is a good predictor of differences in actual broadband diffusion between countries in any year after 1996 (including the PIAAC survey years 2011/2012). In fact, the country-level correlation between the fixed-line infrastructure in 1996 and broadband diffusion in 2012 is very high at 0.79.

However, in some countries, such as Korea, the preexisting voice-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 (see also Bhuller, Havnes, Leuven, and Mogstad, 2013; Akerman, Gaarder, and Mogstad, 2015). 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 the extent of the voice-telephony network in 1996 instead of actual broadband diffusion in 2012 to predict individuals' ICT skills in PIAAC solves these endogeneity problems.

<< Figure 3 about here >>

We implement the 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 our instrument, T_c, has an independent direct effect on individuals' wages at the time of the PIAAC survey or affect wages

[26] The International Telecommunications Union (ITU) is the United Nation's agency for telecommunications.

through a channel other than ICT skills. To dispel concerns about the exogeneity of the traditional voice-telephony network, the vector $\boldsymbol{X_c}$ contains a country's GDP-per-capita level before broadband rollout and its wage level 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.[27] 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).[28] 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.[29]

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.

[27] 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.

[28] 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.

[29] 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 years, 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. When constructing the country-level means, we omit workers from age 60 onward because of differences across countries in retirement and labor-force participation rates.

3.4 Within-Country Instrumental-Variable Model

By design, our international analysis that exploits cross-country variation in the extent of fixed-line networks cannot account for differences in individuals' ICT skills within countries. These differences, however, are substantial in PIAAC; in our estimation sample, the within-country standard deviation in ICT skills is 40.5 points, while the between-country standard deviation is just 8.5 points. Moreover, employing a country-level instrument also comes 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 skills.

In general, differences in broadband diffusion across regions within a country are largely determined by the endogenous decisions of profit-maximizing telecommunication carriers, which are, in turn, influenced by demand factors such as income level, educational attainment, and degree of urbanization. Since these factors may also affect current wages, we exploit the fact that past a certain threshold in the distance between a household and its assigned MDF broadband is no longer feasible (see Section 3.2). Specifically, in West Germany, the general structure of the voice-telephony network dates back to the 1960s when the provision of telephone service was a state monopoly with the declared goal of providing universal telephone service to all German households.[30] While all households connected to an MDF enjoyed voice-telephony services of a similar quality, only those households below a distance to their assigned MDF of 4,200 meters (2.6 miles) could gain access to broadband Internet when a DSLAM was installed.[31] Past this threshold, DSL technology was no longer feasible without replacing parts of the copper wire (typically placed between the MDF and the street cabinet) with fiber wire (see Figure 2). Since this replacement involved costly earthworks

[30] We neglect East Germany since we cannot rule out that location decisions for the MDFs in East Germany, which were made after the reunification in the 1990s, were partly determined by unobserved characteristics of the municipalities that are also correlated with individual wages. See Bauernschuster, Falck, and Woessmann (2014) for details.

[31] A threshold value of 4.200 meters is a consequence of the DSL provision policy of the German telecommunication carrier, the Deutsche Telekom, which only marketed DSL subscriptions at the lowest downstream data transfer rate of 384 kbit/s if the line loss was less than 55 decibel (dB). Since the copper cables connecting a household with the MDF usually came with a diameter of 0.4 mm, a line loss of 55dB was typically reached at a length of about 4,200 meters. As the actual line loss depends on other factors as well, the 4,200-meter threshold is only a fuzzy threshold (Falck, Gold, and Heblich, 2014). This fuzziness in the technological threshold of DSL availability is substantially more severe in other countries, effectively limiting the use of the threshold identification to Germany.

that increased with the length of the bypass, certain West German municipalities were excluded from early broadband Internet access.[32]

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.[33] Following a similar line of argumentation as in the cross-country identification strategy, we expect that PIAAC respondents in municipalities above the 4,200-meter threshold have lower ICT skills because they had less opportunity to accumulate ICT skills due to a lack of high-speed Internet access.

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 to have access to 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).[34]

[32] 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).

[33] 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 kbit/s.

[34] 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 years and drop first-generation migrants.

Similar to the cross-country model, we control for potential direct effects of broadband diffusion on wages by including municipality-level wages of individuals aged 50–59 years, computed from the PIAAC micro data. To account for the fact that wage setting at the regional level in Germany can be affected by local labor-market conditions and the age structure, we add the unemployment rate and the population share of individuals above 65 years in a municipality as control variables.[35]

However, an important threat for the validity of our within-country IV strategy would be if people selectively relocated 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 exact geo-coordinates of the SOEP households in West Germany (excluding Berlin) for the survey waves 2000–2010[36] 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).[37] 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 (6.2 percent) for households from dwellings situated below (above) the threshold. Thus, the relocation rate of above-threshold households is even (albeit insignificantly) *lower* than that of below-threshold households. Furthermore, 93.8 percent of the relocations do not involve a crossing of the threshold. Overall, 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.[38] Moreover, our estimations always employ the

[35] Data come from the German Federal Statistical Office. Note that 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.

[36] 2000 is the year when broadband was first introduced in Germany.

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

[38] 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;

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 Instrument Validity and Sample

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. Otherwise, it may just be spuriously correlated with ICT skills. Since the instrument 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 early phase of extensive broadband diffusion in the early 2000s (which is likely to contribute most to the learning-by-doing effects we identify), almost 60 percent of first-generation immigrants in PIAAC had not yet migrated into the test country in 2000. 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 (Columns (1) and (2)).[39] For first-generation immigrants, however, fixed-line diffusion and ICT skills are not

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 check 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 (using Stata's *cgmwildboot* command for implementation). All results remain robust when employing the wild bootstrap procedure as an alternative to clustering.

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

significantly related (Column (3)).[40] Since we can hardly ascribe their ICT skills to broadband Internet access in the PIAAC test country, we exclude first-generation immigrants from the subsequent analyses.[41]

<< 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 4 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 generally 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 years, who are likely to use technology other than DSL to access the Internet (e.g., LTE/HSPA on smartphones).[42] These results provide a rationale for restricting our main estimation sample to 20–49 year olds.[43]

<< Figure 4 about here >>

In Table 2, we challenge the validity of our identification strategy in another way. Here, we estimate country-level first stage equations replacing ICT skills with various outcomes measured

[40] 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.

[41] Since results are identical when dropping cases where information on the country of birth of the parents ($n = 197$) or the respondent's origin country ($n = 2$) is missing, we include them in the estimation sample.

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

[43] We also performed estimations for other age groups (35–54, 35–65, 16–65), yielding qualitatively similar results to those reported below. Results can be obtained from the authors upon request.

before broadband rollout that potentially affect today's wages. In Columns (1)–(8), we consider both economic variables (i.e., hourly wages, wage growth between 1996 and 2012, years of schooling, and population size) and variables reflecting a country's general technology affinity (i.e., share of high-tech exports, share of STEM graduates, and the extent of the cable TV network[44]) and its specialization on ICT products (i.e., ICT goods trade as a share of total trade), respectively.[45] A significant relationship between the traditional fixed-line network and any of these variables might indicate a violation of the exclusion restriction, that a larger extent of the fixed-line network affects today's wages only through individuals' ICT skills, and not directly in any other way. Reassuringly, the relationships between the instrument and the considered outcomes are neither statistically nor economically significant, lending support that the exclusion restriction holds. Corroborating the results from Table 1 for individual-level ICT skills, there is a very close relationship between the instrument and a country-level measure of ICT skills, significant at the 1 percent level (Column (9)).

<< Table 2 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 validity of our results. Figure 5 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.[46]

<< Figure 5 about here >>

[44] Cable TV networks are an alternative determinant of broadband rollout as they have been upgraded for broadband Internet use in many countries (Czernich, Falck, Kretschmer, and Woessmann, 2011).

[45] All outcomes refer to 1996 unless otherwise noted. Data on wage level, wage growth, ICT goods trade, and STEM graduates are provided by the OECD. Data on years of schooling and population are from Barro and Lee (2010) and refer to 1995. Data on high-technology exports are from the World Bank and data on cable TV diffusion are from ITU.

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

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 3. For comparison, Table 3 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 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.[47]

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.[48] Across specifications, our results indicate significant returns to ICT skills. With all controls (Column (6) of Table 3), 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.[49] 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

[47] Table A-3 reports all first-stage coefficients for the corresponding specifications in Table 3, 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.

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

[49] 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.

equal in the specification with all controls.[50] While all the individual-level control variables enter the regressions with the expected sign[51], 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 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.[52] Although their 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 3 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

[50] 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.

[51] 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.

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

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 3.

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 (e.g., DiNardo and Pischke, 1997). Thus, in our 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 4 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)), while the instrument continues to be a relevant predictor of ICT skills when the other skill domains are accounted for (Columns (6) and (7)). These results indicate that our instrument captures the "right" variation and provide confidence that the returns-to-ICT-skills estimates in Section 4.2 are not biased due to unobserved skills of the PIAAC respondents.[53]

<< Table 4 about here >>

[53] Note that 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. However, returns-to-ICT-skills estimates remain statistically significant and sizeable when including numeracy or literacy skills as an additional control.

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 country-level controls included in our baseline model. 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 that do not require ICT skills, that is, occupations where computers are not at all or only infrequently used. To identify these occupations, we make use of the fact that 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.[54] Judging by this index, workers in elementary occupations make least use of computers; consequently, we would expect that returns to ICT skills are small or even nonexistent there.[55] 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 in 2012 and that are

[54] 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 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.

[55] 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.

not captured by the two included country-level controls.[56] 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 current cellphone diffusion to proxy for Internet access technologies other than DSL.[57] The results, shown in Columns (1) to (7) of Table 5, demonstrate that the estimated 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.[58]

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 (8) of Table 5).[59]

<< Table 5 about here >>

[56] 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.

[57] All additional country-level variables refer to 2012 unless otherwise noted. Data on union density, employment protection legislation, and youth unemployment rate are provided by the OECD. 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). The public-sector share is calculated from the PIAAC data. The service-sector share is provided by the World Bank and Statistics Canada. The share of persons that completed tertiary education is taken from Barro and Lee (2010) and refers to 2010. Data on mobile telephone diffusion are from ITU. See Table A-2 for descriptive statistics.

[58] 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.

[59] 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.

In Table 6, 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.[60] Further, 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.[61] 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.[62]

<< Table 6 about here >>

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

[61] 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.

[62] 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), which is in line with the seniority-based and rather compressed pay scale in the public sector. Results are available on request.

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.

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—where we also exploit historical peculiarities in the structure of the voice-telephony network as a source of plausibly exogenous variation in ICT skills (see Section 3.4). In Table 7, 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 even 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.[63] Although we do not find evidence that the mobility pattern is systematically related to our instrument (see Section 3.4), it is a source of measurement error leading to an attenuation bias in the first-stage regression. To address a potential weak-

[63] As shown in Section 3.4, 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.

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.[64]

Turning to the second stage of our IV estimation (see the upper part of Table 7), 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)).[65] The returns are somewhat larger than the corresponding estimate in the cross-country sample, which is consistent with the evidence in Hanushek, Schwerdt, Wiederhold, and Woessmann (2015) that Germany is one of the countries with the highest returns to cognitive skills worldwide.

<< Table 7 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 8 presents placebo tests analogous to those in Table 4 for the cross-country sample. While neither numeracy nor literacy skills are systematically affected by the threshold instrument and even show positive coefficients throughout specifications, the relationship between ICT skills and the instrument remains significantly negative even conditional on the other skill domains.

<< Table 8 about here >>

[64] 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.

[65] The three-equation estimations in Table A-5 indicate that the reduced-form first-stage estimates in Table 7 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.

6. Task Content of Occupations and Returns to ICT Skills

In the following we will look at a potential mechanism driving the positive wage returns to ICT skills, namely, that recent technological change is complementary to nonroutine abstract tasks, which use and reinforce ICT skills. 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.[66] The authors ask what kind of tasks computers execute that substitute for or complement tasks performed by workers. Therefore, instead of using conventional labor group distinctions (low-skilled, medium-skilled, and high-skilled; production and nonproduction; or blue-collar and white-collar), they propose a measurement of tasks that provides an intuitive and testable explanation of the relationship between the introduction of new technologies and the demand for heterogeneous labor. The basic idea is that computers substitute for routine tasks (those that can be accomplished by following explicit rules) and are complementary to nonroutine abstract tasks (such as problem solving and coordination). The underlying reasoning is that routine tasks embody explicit knowledge that can be relatively easily programmed, which is not the case for nonroutine tasks. Moreover, an increase 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.[67]

Trends toward a rising importance of 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 assess the ICT skills of workers in occupations that make intense use of abstract tasks and compare them to the ICT skills of workers with little abstract task intensity.[68] We also investigate whether the proliferation of personal computers is complementary to abstract tasks and whether it substitutes for routine tasks, as found in Autor, Levy, and Murnane (2003). Specifically, we correlate abstract and routine task intensity, respectively, with the index of computer use at work introduced

[66] Related work also suggests that the skill structure of developed economies has changed remarkably since the second half of the 20th century. Educational upgrading was a prevalent trend and widespread evidence points toward increases in skill premia (e.g., Acemoglu, 2003; Goldin and Katz, 2009) and in wage inequality (e.g., Autor, Katz, and Kearney, 2008; Dustmann, Ludsteck, and Schönberg, 2009; Card, Heining, and Kline, 2013; Autor, 2014).

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

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

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).[69]

Figure 6 shows the results from this analysis. Both ICT skills and computer use systematically vary with a job's 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 intensive 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.[70]

<<Figure 6 about here >>

[69] 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." 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.

[70] 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.

Although being purely descriptive, the results in Figure 6 have two important implications: First, they 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. Second, they suggest that the proliferation of computers is potentially a mechanism behind the positive returns to ICT skills in modern labor markets. Jobs that are dominated by abstract tasks pay substantial wage premia[71], and having high ICT skills seems to be a necessary prerequisite to enter these well-paid jobs.

7. Conclusion

This paper investigates 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 cross-country differences in the extent of traditional voice-telephony networks that were upgraded for fast Internet use. The underlying idea is that ICT skills are developed through learning by doing, for which having access to the Internet is a precondition. We show that voice-telephony networks from before the emergence of broadband are indeed a strong predictor of current 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, the general economic condition before widespread broadband rollout, and a country's current wage level.

Our results indicate that better ICT skills are systematically related to higher wages, with a one standard deviation increase in ICT skills leading to a 7.5 percent increase in wages. A placebo test showing that preexisting voice-telephony networks cannot explain any variation in numeracy or literacy skills 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 that also exploits 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.

[71] In our sample, jobs which are intensive in abstract tasks pay on average 25 percent higher wages than jobs that involve relatively little abstract tasks. 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.

By showing that ICT skills are rewarded quite substantially 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.

This paper also sheds light from a new angle on the discussion about the digital divide, which describes the notion that there is social inequality in access to the Internet. For instance, linking data from the 2013 American Community Survey with the most recent version of the National Broadband Map, President Obama's Council of Economic Advisors shows that Black and Hispanic households in the U.S. are 16 and 11 percentage points less likely to have an Internet connection than white households, respectively (CEA, 2015). The fundamental insight of this paper that the ability to function in ICT-technology-rich environments can be promoted by providing access to this technology suggests that the efforts by policy-makers worldwide to expand broadband Internet access may not only close the gap in Internet access, but also lead to a convergence in the skills to master digital technologies. At the same time, our research also puts a number on the economic benefits foregone for those who are lacking Internet access due to informational or financial reasons.

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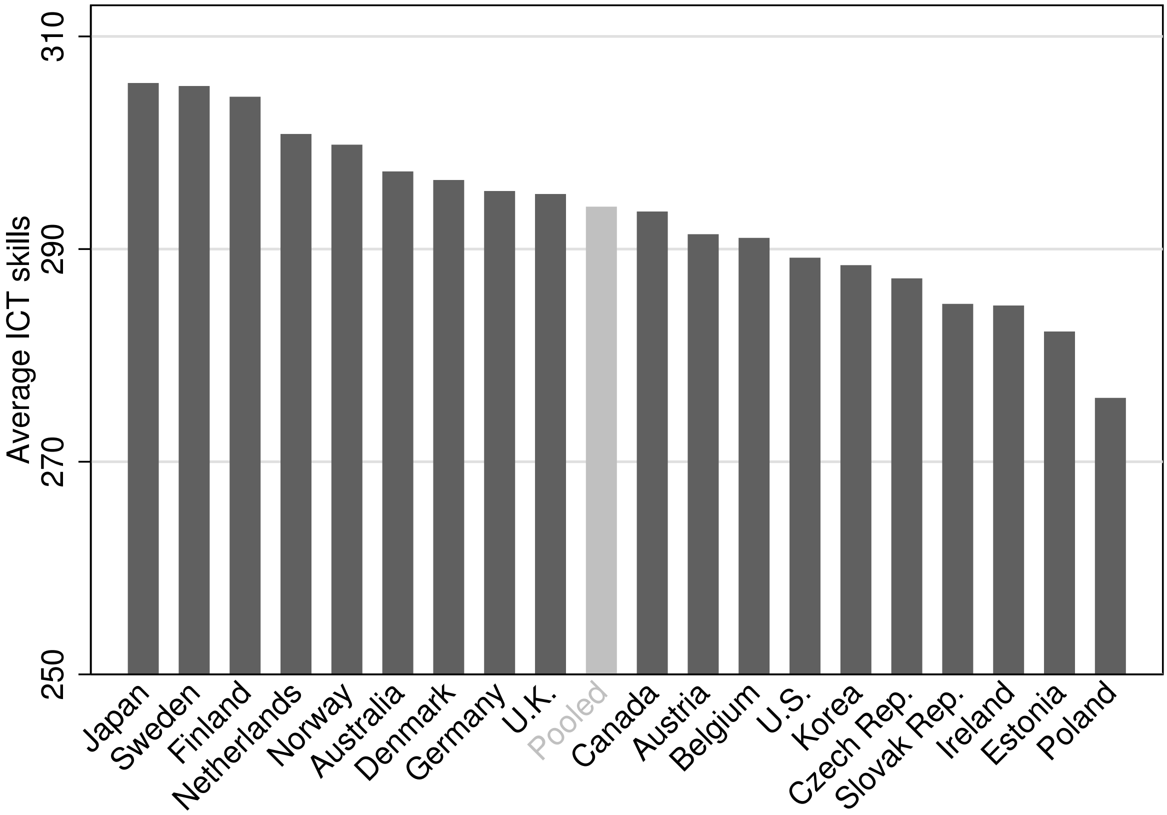
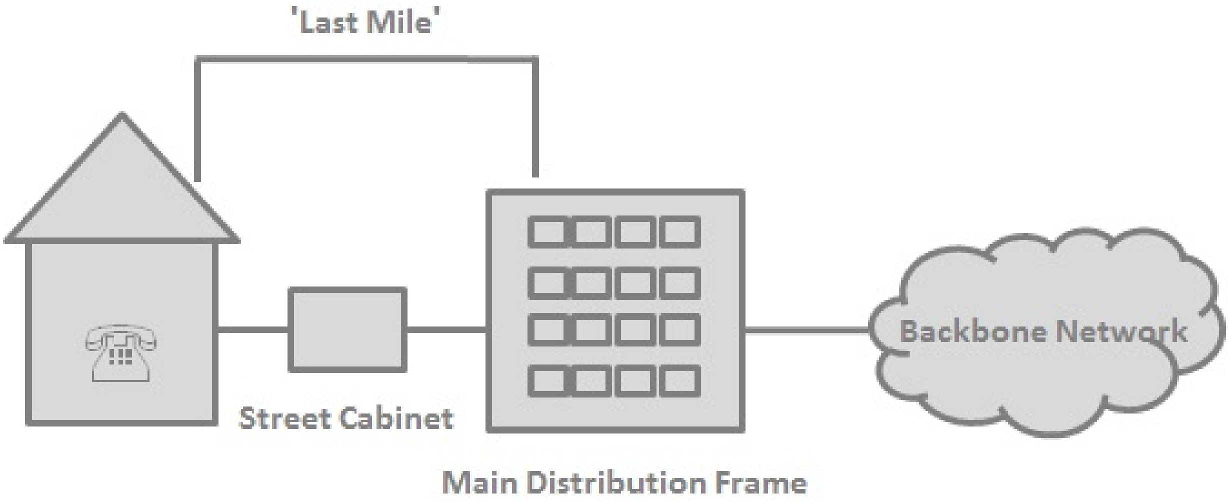
Figures and Tables

Figure 1: ICT Skills Around the World



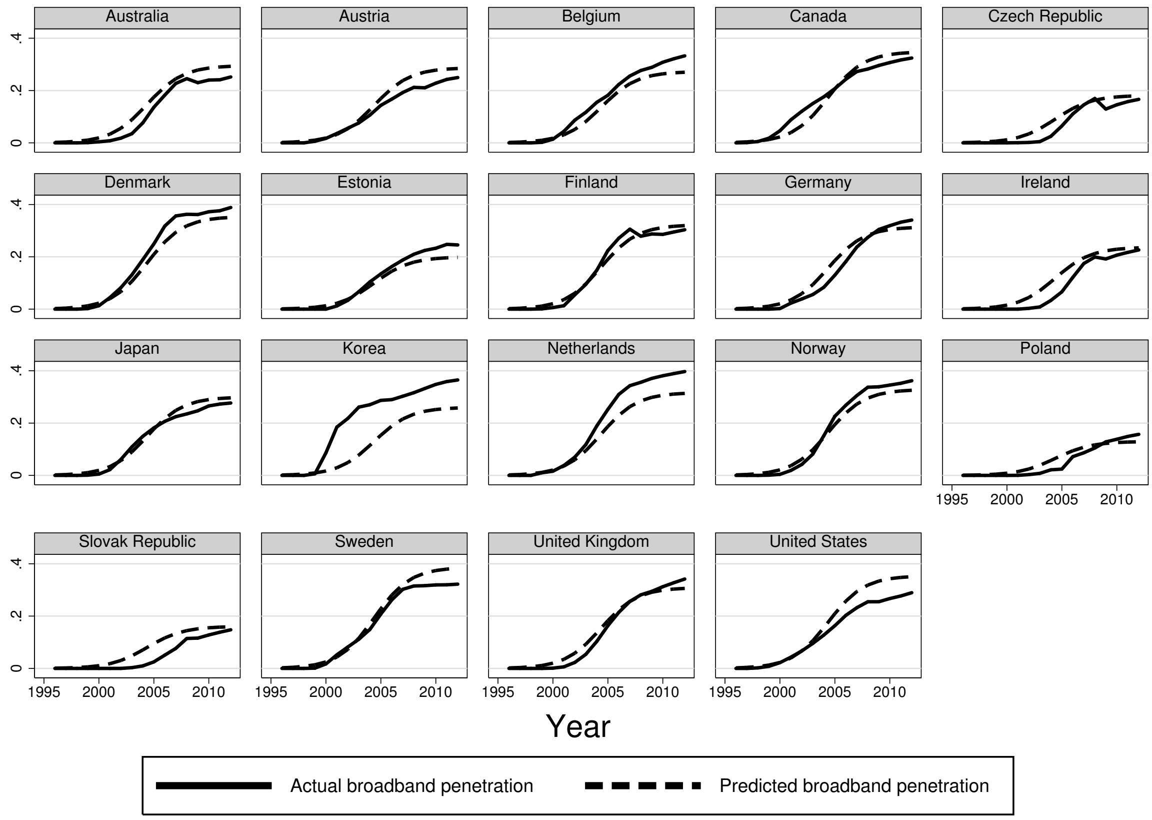
Notes: Average ICT skills across countries. Sample: employees aged 20–49 years, no first-generation immigrants. *Data source:* PIAAC.

Figure 2: The Structure of a DSL Network



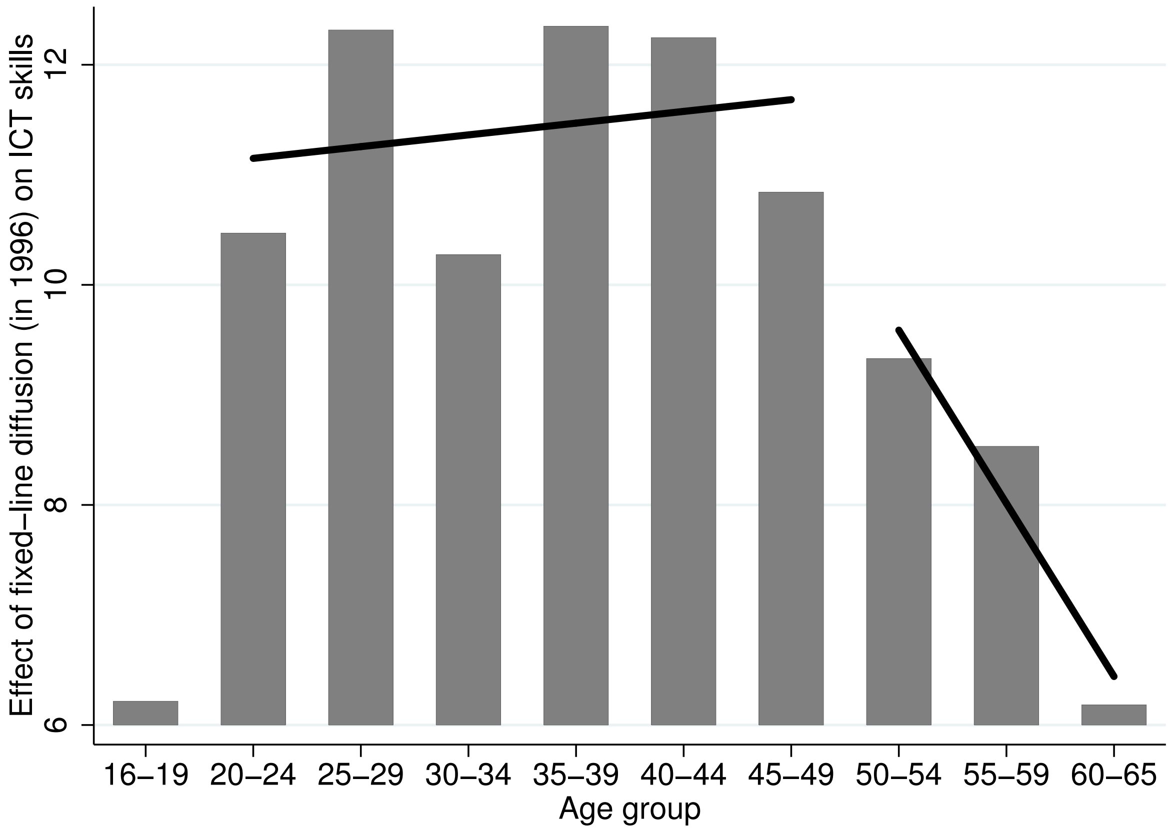
Notes: The figure shows the structure of a DSL network that relies on the "last mile" of the preexisting fixed-line voice-telephony network. The "last mile" consists of copper wires connecting every household via the street cabinet to the main distribution frame. At the main distribution frame, a DSLAM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

Figure 3: Broadband Diffusion Across Countries: Actual and Predicted Curves, 1996–2012



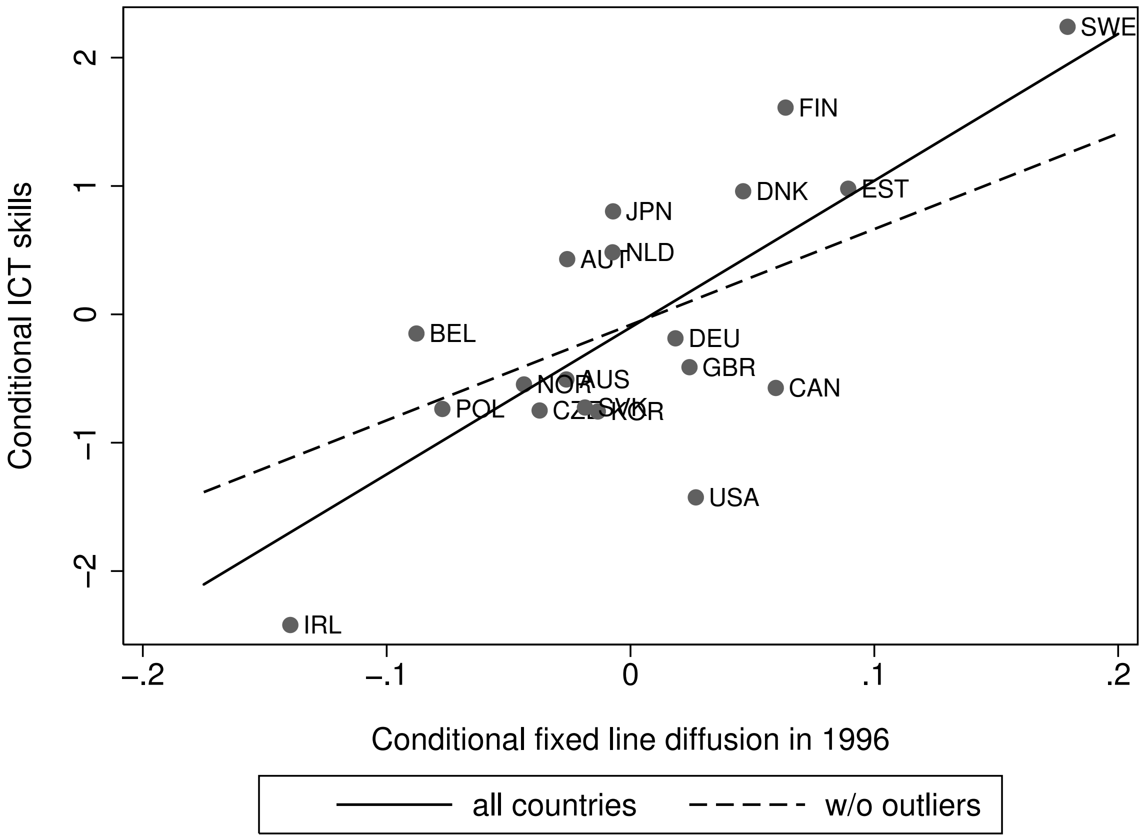
Notes: Actual broadband penetration is measured as the number of broadband subscribers per inhabitant in 2012. Predicted broadband diffusion is derived from nonlinear least squares estimation of a diffusion curve based on the voice-telephony penetration rate (telephone access lines per inhabitant) in 1996. See Section 3.3 for details. *Data sources:* ITU, OECD.

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



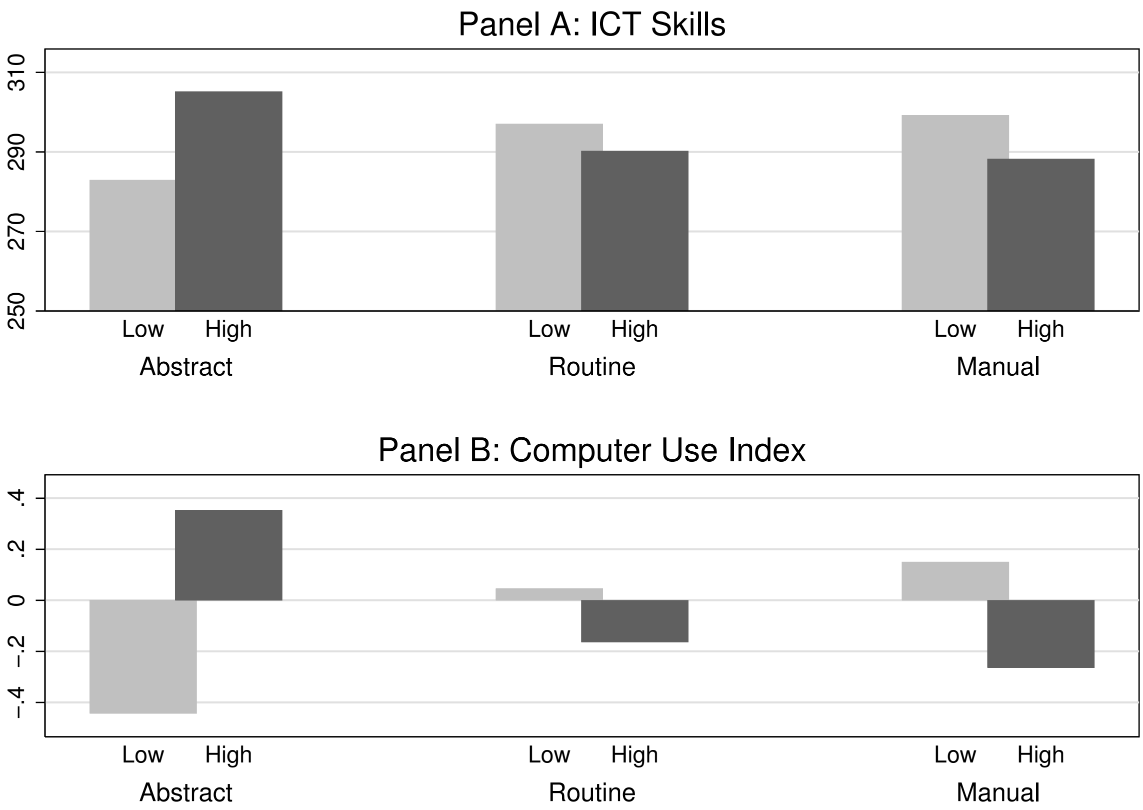
Notes: Coefficient estimates on fixed-line voice-telephony diffusion (in 1996) for indicated five-year age groups in a regression of ICT skills (standardized to std. dev. 1 across countries) on fixed-line diffusion and all control variables included in Table 3, Column (6). Regression weighted by sampling weights (giving same weight to each country). Sample: employees, no first-generation immigrants. 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 5: Preexisting Fixed-Line Diffusion and ICT Skills (First Stage)



Notes: Added-variable plot from a regression of ICT skills on fixed-line voice-telephony diffusion (in 1996) and all control variables included in Table 3, Column (6). Sample: employees aged 20–49 years, no first-generation immigrants. Based on individual-level regressions (weighted by sampling weights) 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 6: ICT Skills and Computer Use by Occupational Task Content



Notes: Sample: employees aged 20–49 years, no first-generation immigrants; 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. *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. immigrants	1st-gen. immigrants
	(1)	(2)	(3)
Fixed-line diffusion in 1996	11.996***	9.638***	–1.343
	(1.658)	(1.419)	(1.521)
GDP per capita in 1996 (log)	1.169*	0.951*	1.110
	(0.610)	(0.540)	(1.170)
Average wage level 50_59 (log)	–3.156***	–2.242***	–2.431**
	(0.722)	(0.627)	(1.110)
Experience	–0.075**	–0.065	–0.054
	(0.027)	(0.040)	(0.057)
Experience^2 (/100)	–0.103	–0.001	0.059
	(0.076)	(0.124)	(0.151)
Female	–0.952***	–0.709***	–0.887***
	(0.104)	(0.170)	(0.200)
Years of schooling	0.673***	0.713***	0.692***
	(0.027)	(0.030)	(0.048)
R squared (adjusted)	0.18	0.18	0.14
Individuals	36,870	3,999	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 years. 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. *2nd-gen. immigrants:* mother, father, or both born abroad; participant born in country of residence. *1st-gen. immigrants:* participant born abroad; at least one parent as well. *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-USD and obtained from the OECD. *Average wage level 50_59 (log)* is the mean wage (in PPP-USD) of employees aged 50–59 years, without first-generation immigrants, 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: Does Preexisting Fixed-Line Diffusion Predict Outcomes in the Pre-Broadband Era?

Dependent variable indicated in column heading	Economic indicators (1996)				Technology indicators (1996)				
	Wage level	Wage growth	Years schooling	Population	%High-tech exports	%ICT trade	%STEM graduates	Cable TV diffusion	ICT skills (2012)
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Fixed-line diffusion in 1996	–0.304	0.006	–0.784	0.042	–0.347	–0.019	0.088	0.509	6.082***
	(0.418)	(0.528)	(2.517)	(0.093)	(0.349)	(0.240)	(0.203)	(0.344)	(1.266)
GDP per capita in 1996 (log)	0.256	–0.106	1.390	0.045	–0.103	–0.103	–0.070	–0.277*	0.929
	(0.230)	(0.220)	(1.349)	(0.043)	(0.095)	(0.078)	(0.208)	(0.141)	(0.614)
Average wage level 50_59 (log)	0.913***	–0.194	–0.984	–0.032	0.379**	0.159	–0.053	0.161	–1.183**
	(0.206)	(0.247)	(1.303)	(0.038)	(0.160)	(0.107)	(0.081)	(0.112)	(0.431)
R squared	0.90	0.37	0.05	0.11	0.52	0.23	0.10	0.23	0.67
Countries	19	19	19	19	18	18	15	19	19

Notes: Country-level ordinary least squares regressions. Outcomes refer to 1996 unless otherwise noted (broadband Internet first appeared in Canada in 1997). Average wages in Column (1) are measured in logs and are in PPP-USD. Wage growth in Column (2) is between 1996 and 2012. Data on years of schooling in Column (3) and population in Column (4) refer to 1995; population is in millions. High-technology exports (as a share of manufactured exports) in Column (5) are the top 10 manufactured products with the highest embodied R&D spending relative to the value of shipments, such as in aerospace, computers, pharmaceuticals, scientific instruments, and electrical machinery (Mani, 2004); data not available for Belgium. ICT goods trade in Column (6) is measured as a share of total trade; data not available for Estonia and refer to 1997 in the Slovak Republic. STEM graduates (as a share of all university graduates) in Column (7) include graduates in Natural Science, Medical Science, Mathematics, Computer Science, Engineering, and Architecture; data not available for Estonia, Korea, Poland, and the Slovak Republic. Cable TV diffusion in Column (8) is measured as cable television subscribers per inhabitant. ICT skills in Column (9) refer to 2012 and are measured as the country-level average (normalized with std. dev. 1) of ICT skills of employees aged 20-49 years, without first-generation immigrants. See text for details on data sources. *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-USD. *Average wage level 50_59 (log)* is the mean wage in 2012 (in PPP-USD) of employees aged 50–59 years, without first-generation immigrants. Robust standard errors in parentheses. Significance levels: * p<0.10, ** p<0.05, *** p<0.01. *Data sources:* Barro and Lee (2010), ITU, OECD, PIAAC, World Bank.

Table 3: 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 years, no first-generation immigrants. Dependent variable, *log gross hourly wage*, is measured in PPP-USD. 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-USD. *Average wage level 50_59 (log)* is the mean wage (in PPP-USD) of employees aged 50–59 years, without first-generation immigrants. 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 4: 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)
Country characteristics	X	X	X	X	X	X	X
Individual characteristics	X	X	X	X	X	X	X
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 years, no first-generation immigrants. 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. 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. 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 5: Returns to ICT Skills: Robustness

Second stage (Dependent variable: log gross hourly wage)								
	Further country controls (2012)							No post-com.
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
ICT skills	0.059***	0.077***	0.050***	0.077***	0.068***	0.080***	0.069***	0.082***
	(0.014)	(0.011)	(0.012)	(0.011)	(0.013)	(0.012)	(0.013)	(0.021)
Union density	0.209***							
	(0.081)							
Employment protection		0.017						
		(0.023)						
Public sector			0.774***					
			(0.220)					
Youth unemployment rate				0.302				
				(0.248)				
Service share					–0.397*			
					(0.225)			
Share tertiary educated						–0.497		
						(0.373)		
Mobile diffusion							0.127*	
							(0.065)	
Country characteristics	X	X	X	X	X	X	X	X
Individual characteristics	X	X	X	X	X	X	X	X
First stage (Dependent variable: ICT skills)								
Fixed-line diffusion in 1996	10.235***	12.558***	11.332***	11.486***	11.912***	12.023***	10.608***	9.986***
	(1.774)	(1.460)	(1.893)	(1.493)	(1.631)	(1.616)	(1.433)	(1.902)
Instrument F statistic	33.3	74.0	35.8	59.2	53.4	55.4	54.8	27.6
Individuals	40,869	40,869	40,869	40,869	40,869	40,869	40,869	33,391
Countries	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 years, no first-generation immigrants. 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 PPP-USD. 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. All country-level control variables refer to 2012 unless otherwise noted. *Union density:* share of wage and salary earners who are trade union members; data refer to 2011 in Korea. *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 years. *Service sector:* share of service sector in the GDP. *Share tertiary educated:* share of population that completed a tertiary education; data refer to 2010. *Mobile diffusion in 2012:* mobile-cellular telephone subscriptions per inhabitant in 2012. See text for details on data sources. 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:* Barro and Lee (2010), ITU, OECD, PIAAC, Statistics Canada, World Bank.

Table 6: 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 years, no first-generation immigrants. Column (5) is without Canada because the health variable is not reported. Dependent variable in second stage, *log gross hourly wage*, is measured in PPP-USD. 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 7: Returns to ICT Skills: Within-Country Baseline Estimates

Second stage (Dependent variable: log gross hourly wage)						
	Full sample			No own MDF sample		
	(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: Two-stage least squares estimation weighted by sampling weights (giving same weight to each country). Sample: West German employees aged 20–49 years, no first-generation immigrants. 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 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 18–65 years), population share of individuals older than 65, and average municipality-level wage of workers aged 50–59 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 8: Within-Country Placebo Test

Panel A: Full Sample

Dependent variable: cognitive skills in	Numeracy (1)	Literacy (2)	ICT (3)	ICT (4)
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

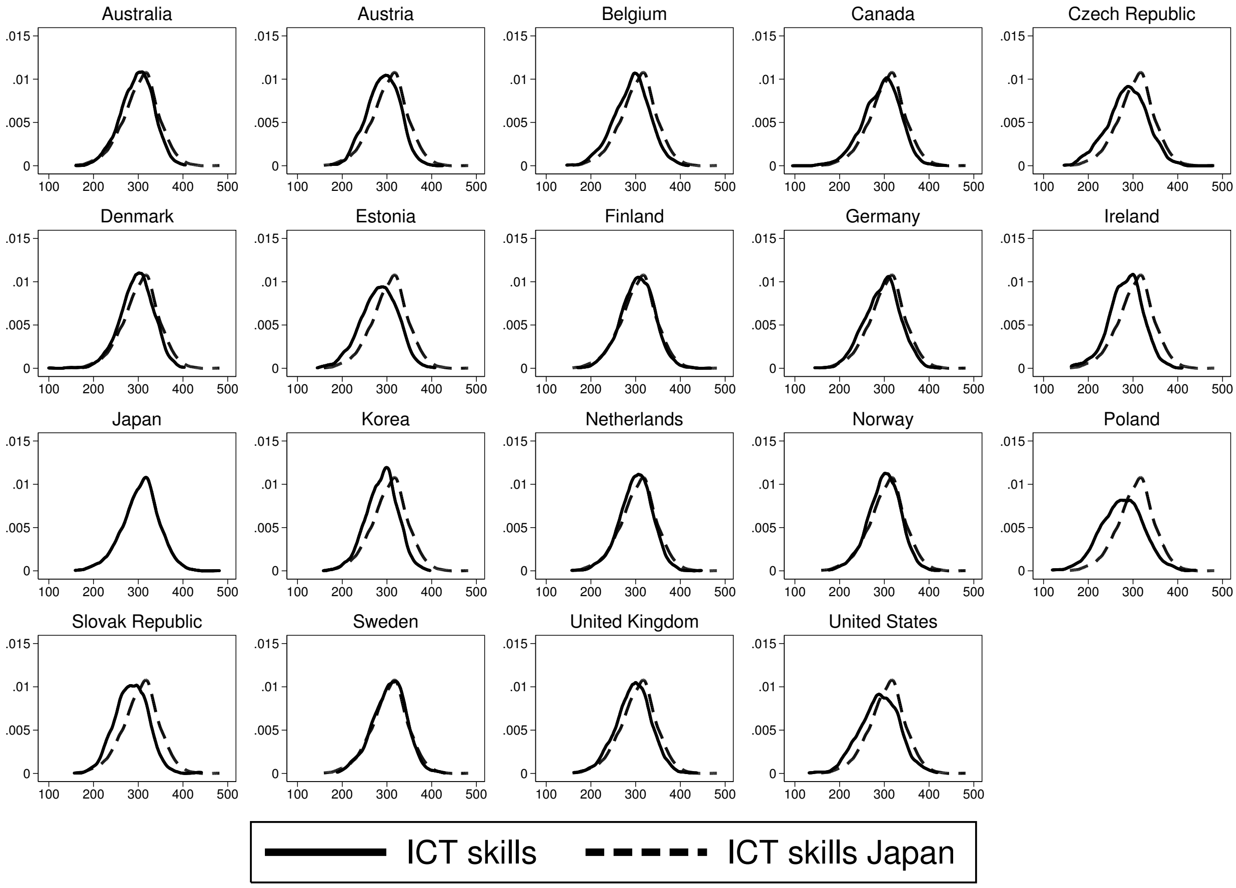
Panel B: No Own MDF Sample

Dependent variable: cognitive skills in	Numeracy (1)	Literacy (2)	ICT (3)	ICT (4)
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 years, no first-generation immigrants. 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:* is equal to 1 if a municipality is more than 4,200 meters away from its MDF (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 18–65 years), population share of individuals older than 65, and average municipality-level wage of workers aged 50–59 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.

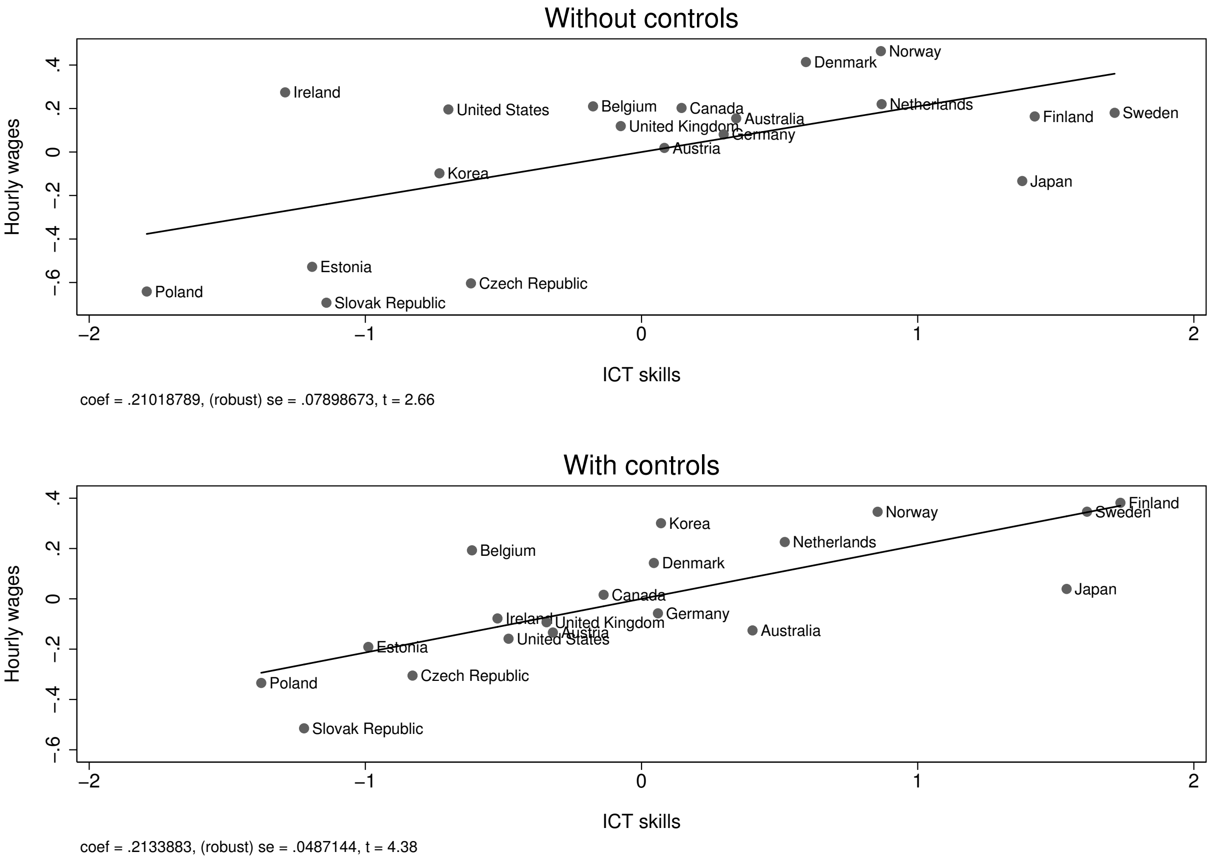
Appendix

Figure A-1: ICT Skills Within Countries



Notes: Smoothed kernel density plots. 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 years, no first-generation immigrants. *Data source:* PIAAC.

Figure A-2: Returns to ICT Skills: Country-Level Least Squares Results



Notes: Sample: employees aged 20–49 years, no first-generation immigrants. 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-USD)	(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-USD)	(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 years, no first-generation immigrants. 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	1999	1997	2000	1999	2001	1999	2000
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
Union density	0.32	0.18	0.27	0.55	0.27	0.13	0.67	0.06	0.69	0.18
Employment protection	2.26	1.99	2.44	2.99	1.51	2.66	2.32	2.07	2.17	2.84
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
Service sector	0.69	0.69	0.70	0.76	0.70	0.75	0.60	0.67	0.70	0.68
Share tertiary educated	0.16	0.22	0.09	0.20	0.28	0.06	0.13	0.18	0.13	0.13
Mobile diffusion in 2012	1.23	1.06	1.61	1.11	0.80	1.27	1.18	1.60	1.72	1.12

	Ireland	Japan	Korea	Netherl.	Norway	Poland	Slovak R.	Sweden	U.K.	U.S.
First emergence of broadband	2002	1999	1999	1999	1999	2001	2003	1999	2000	1998
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 (/1000)	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
Union density	0.31	0.18	0.10	0.18	0.53	0.13	0.17	0.68	0.26	0.11
Employment protection	2.07	2.09	2.17	2.88	2.31	2.39	2.16	2.52	1.76	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
Service sector	0.71	0.73	0.59	0.76	0.58	0.64	0.72	0.61	0.79	0.78
Share tertiary educated	0.20	0.24	0.17	0.16	0.15	0.09	0.07	0.17	0.14	0.32
Mobile diffusion in 2012	1.07	1.11	1.09	1.18	1.17	1.40	1.12	1.25	1.35	0.95

Notes: Only country-level characteristics reported. *First emergence of broadband:* year of introduction of broadband Internet; data on broadband diffusion in Estonia available only from 2001 onward. *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-USD (divided by 1,000) with base year 2005. *Average wage level 50_59* is the mean wage (in PPP-USD) of employees aged 50–59 years, without first-generation immigrants. *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 years. *Service sector:* share of service sector in the GDP. *Share tertiary educated:* share of population that completed a tertiary education; data refer to 2010. *Mobile diffusion:* mobile-cellular telephone subscriptions per inhabitant in 2012. See text for details on data sources. Pooled specification gives same weight to each country. *Data sources:* Barro and Lee (2010), ITU, OECD, PIAAC, Statistics Canada, World Bank.

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 3, 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 years, no first-generation immigrants. Dependent variable in third stage, *log gross hourly wage*, is measured in PPP-USD. 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 (broadband subscribers per inhabitant) in 2012 (see Figure 3). *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 years, no first-generation immigrants. Columns (1)–(3) show results for all West German municipalities in the sample; Columns (4)–(6) restrict the 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:* is equal to 1 if a municipality is more than 4,200 meters away from its MDF (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 18–65), population share of individuals older than 65, and average municipality-level wage of workers aged 50–59 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.