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RETURNS TO ICT SKILLS

Education Working Paper No. 134

By Oliver Falck, Alexandra Heimisch and Simon Wiederhold.

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The Annex containing Figures and Tables is available in pdf format only.

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Abstract

How important is mastering information and communication technologies (ICT) in modern labour markets? We present the first evidence on this question, drawing on unique data that provide internationally comparable information on ICT skills in 19 countries from the OECD Programme for the International Assessment of Adult Competencies (PIAAC). Our identification strategy relies on the idea that Internet access is important in the formation of ICT skills, and we implement instrumental-variable models that leverage exogenous variation in Internet availability across countries and across German municipalities. ICT skills are substantially rewarded in the labour market: returns are at 8% for a one-standard-deviation increase in ICT skills in the international analysis and are almost twice as large in Germany. 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. Our results further suggest that the proliferation of computers complements workers in executing abstract tasks that require ICT skills.

Résumé

Quelle est l'importance de la maîtrise des technologies de l'information et de la communication (TIC) sur les marchés du travail modernes ? Nous présentons ici les premières réponses à cette question, à partir de données uniques offrant des informations comparables à l'échelle internationale sur les compétences en TIC dans 19 pays. Notre stratégie d'identification repose sur l'idée que l'accès à Internet joue un rôle important dans la formation des compétences en TIC, et nous appliquons des modèles à variables instrumentales utilisant la variation exogène de l'accès à Internet entre les pays et entre différentes municipalités allemandes. Les compétences en TIC font l'objet d'une reconnaissance substantielle sur le marché du travail : les rendements s'établissent ainsi à 8 % pour une augmentation d'un écart-type des compétences en TIC dans l'analyse internationale et sont presque deux fois plus élevés en Allemagne. Des estimations placebo montrent qu'un accès exogène à Internet ne constitue pas un facteur explicatif des compétences en numératie ou en littératie, semblant indiquer que notre identification d'une variation est indépendante des aptitudes générales des individus. Nos résultats suggèrent en outre que la multiplication du nombre d'ordinateurs assiste les travailleurs dans l'exécution de tâches abstraites nécessitant des compétences en TIC.

Note for Readers

Readers should note that, in this paper, the term 'ICT skills' is used to refer to, among other things, the skills measured by the assessment of 'problem solving in technology-rich environments' in the OECD PIAAC study.

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, convincing empirical evidence on how the labour 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 provides the first systematic assessment of the wage returns to ICT skills.[2]

Our identification strategy is based on the idea that ICT skills are developed by performing ICT-related tasks, which is facilitated when access to the Internet is available.[3] We thus estimate instrumental-variable (IV) models that exploit exogenous variation in the probability of having Internet access either across countries or across small geographical areas within a single country. In the cross-country model, this variation stems from international differences in the rollout of pre-existing voice-telephony networks which determine the timing of introduction and diffusion of high-speed Internet via broadband. These networks affect only the supply side of broadband diffusion in a country and therefore rule out demand-side effects based on differences in wealth and broadband-deployment policies (Czernich, 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 availability of broadband Internet about 40 years later. Beyond a certain distance threshold, high-speed Internet access was not feasible without major infrastructure investment, which excluded a considerable share of West German municipalities from early broadband Internet access (Falck, Gold, and Heblich, 2014).[4]

We find that the extent and technical peculiarities of the pre-existing voice-telephony infrastructure 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 confidence in our IV strategy. For instance, 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, human capital endowment, and technological specialisation 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. Importantly, pre-existing 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 general ability) on wages.[5]

Drawing only on variation in ICT skills attributable to exogenously determined broadband access, both IV 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 an

8% increase in employee wages. In Germany, estimated returns to ICT skills are even larger at 15%. 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.

Subsample analyses show that returns to ICT skills are negligible in occupations that involve little or no ICT skills to perform the required tasks and are highest in occupations that heavily rely on ICT skills. This indicates that our estimated returns to ICT skills do not just reflect the wage effects of some unobserved country-specific factors. Furthermore, estimated returns are significantly higher in the private sector than in the public sector and tend to decrease with age. Finally, we show that estimated returns change only little when additional variables that affect wages are included, providing confidence that our identification strategy effectively addresses omitted-variable bias.

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 automatisation—toward problem-solving and complex communication tasks (typically called "non-routine 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. This is suggestive evidence that ICT skills are 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 (requiring ICT skills) and abstract tasks allows workers possessing high ICT skills to benefit from the wage premiums paid in abstract jobs.[7]

Our paper is directly related to the literature on the wage returns to computer skills.[8] This literature typically had to rely on self-reported measures of computer *use*, for instance, from the United States. Current Population Survey (e.g., Krueger, 1993), implicitly assuming that workers who embody more skills are allocated to jobs in which computer skills are required. A few papers have used self-reported measures of computer *knowledge* or *skills*, provided, for instance, in the German Qualification and Career Survey (e.g. DiNardo and Pischke, 1997) or in the British Skills Survey (e.g. Borghans and ter Weel, 2004). Still, these measures are also very imperfect proxies for a worker's true skills because they are very crude, typically allowing for only a few answering categories;[9] suffer from reporting bias, and assume that workers are aware of the full skill distribution in the population. Moreover, existing worker surveys are not harmonized across countries, which renders an international analysis impossible. Furthermore, the returns from one or two decades ago may no longer be good indicators of the situation in economies that have undergone substantial technological change (discussed in, for instance, Autor, Levy, and Murnane, 2003; Goldin and Katz, 2008; Acemoglu and Autor, 2011). By using recent assessment data of workers' ICT skills that are internationally comparable, we provide novel insights into the value of mastering modern information and communication technologies in the labour market.

Previous literature also highlights the empirical challenges of attempting to estimate causal effects of computer skills. For example, an influential paper by DiNardo and Pischke (1997) suggests that computer users possess unobserved skills that might have little to do with computers per se but that increase their productivity. 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 labour-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.[10] 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 IV 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 using exogenous variation in domain-specific skills 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, with positive effects only for some types of uses (Falck, Mang, and Woessmann, 2015). Our results suggest that developing ICT skills through e-learning (as shown, for instance, in Malamud and Pop-Eleches, 2011) might prove beneficial for students' future labour-market outcomes, even if e-learning itself is not associated with better school grades.

The paper is organized as follows. Section 2 describes the PIAAC data and the assessment of ICT skills. Section 3 outlines our IV strategy and discusses the sample restrictions. Section 4 provides an analysis of the validity of our instruments. Section 5 presents the returns-to-ICT-skills estimates and reports results from subsample analyses and a number of robustness checks. Section 6 describes 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 Organisation 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% of worldwide GDP.[11] 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, hourly wages as well as skill use at home and at work. This information is derived from a detailed background questionnaire completed by the PIAAC respondents prior to the skills assessment. The survey was administered by trained interviewers either in the respondent's home or at a location agreed upon between the respondent and interviewer.[12]

PIAAC provides measures of cognitive skills in three domains: literacy, numeracy, and ICT (called "problem solving in technology-rich environments" in the survey). PIAAC measures each of the skill domains on a 500-point scale.[13] The individual-level correlation of ICT skills with literacy (numeracy) is 0.77 (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.[14]

We focus on *ICT skills*, defined as "using digital technology, communication tools and networks to acquire and evaluate information, communicate with others and perform practical tasks" (OECD, 2013, p. 86).[15] To assess ICT skills, participants were given a series of problem scenarios and asked to find solutions to them using ICT-based applications such as an Internet browser and web pages, e-mail, word processing, and spreadsheet tools. 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.[16] In general, ICT skills as assessed in PIAAC measure the extent to which a participant is capable of using modern information and communication tools to get along in a digital world. By contrast, the ICT test in PIAAC does not reflect proficiency in more specific computer skills like advanced programming.

ICT skills were assessed in a computer-based mode, so some basic knowledge regarding the use of computers was required to participate in the ICT skill test; 9.3% of all PIAAC participants indicated in the background questionnaire that they had no prior computer experience and thus these participants did not take part in the computer-based assessment. Instead, they took the survey via pencil and paper, and only their numeracy and literacy skills were tested. Participants who reported at least basic knowledge of computer-based applications were issued an ICT core test, which assessed basic ICT competencies, such as using a keyboard/mouse or scrolling through text on the screen; 4.9% of all participants did not pass this test and thus were also excluded from the ICT skills assessment. Moreover, 10.2% 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.[17]

Persons without an ICT skills score are excluded from our sample.[18] Furthermore, the assessment of ICT skills was an international option. Cyprus[19], France, Italy, and Spain did not take part in the ICT skills assessment, which leaves us with data for 19 countries.[20] For reasons related to our identification strategy (see Section 3), our main analysis focuses on 20–49 year-old natives and second-generation immigrants. After imposing these restrictions, the sample includes 40 670 individual-level observations.[21]

Figure 1 depicts average ICT skills in our estimation sample by country. The average level of ICT skill is 293 points, with an individual-level standard deviation of 40 points.[22] 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), Ireland, and Korea 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% of an individual-level standard deviation.[23] The low level of ICT skills in Korea may appear surprising because the Korean government has exerted great financial effort to roll out broadband Internet (see also Section 3.3). However, a closer inspection of the data reveals that the low average proficiency in Korea is mainly driven by the very low ICT skills of the older respondents in our sample (45–49 years), who fall substantially short of international performance and, together with Estonia and Poland, are at the bottom of the international league tables. However, the ICT skills of Korean respondents aged 20–24 years (302 points) are well above the international average for this age group (297 points).[24] 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.[25]

Table A-1 shows the descriptive statistics of participants' characteristics for the pooled international sample and separately for each country. The size of the estimation sample ranges from 1 356 persons in the Slovak Republic to 7 474 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-USD) across countries. Workers in Norway, Denmark, and Ireland earn the highest wages and workers in the post-communist countries are paid the least, with the difference between the highest-paying country (Norway) and lowest-paying country (the Slovak Republic) amounting to 160% of an international standard deviation. There is also considerable cross-country variation in our estimation sample in years of schooling and work experience.

3. Identification Strategy

3.1 Empirical Model

We estimate returns to ICT skills in a general Mincer framework (Mincer 1970, 1974) that relates a person's human capital to earnings in the labour 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 percentage when ICT skills increase by one standard deviation.[26]

In this basic regression framework, β_1 can hardly be interpreted as the causal effect of ICT skills on wages. The most obvious reasons for β_1 being a biased estimate of the true returns to ICT skills are measurement error, reverse causality, and omitted variables (for a discussion, see Hanushek, Schwerdt, Wiederhold, and Woessmann, 2015). Measurement error may occur if cognitive skills in PIAAC are just an error-ridden measure of the human capital relevant in the labour market, and these 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 solved tasks correctly or incorrectly simply by chance. This measurement error in the assessment of an individual's ICT skills will bias the coefficient on ICT skills toward zero.[27] 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 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.[28] 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[29], relies on the copper wires of the voice-telephony network connecting households with the main distribution frame (MDF).[30] The voice-telephony networks were typically planned and rolled out by state monopolies and decisions were thus rather taken on the basis of political instead of commercial considerations. 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 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 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 earlier and reached a larger share of the population than countries lagging behind in fixed-line infrastructure (see Section 3.3).

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 feasibility of the DSL technology 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 (see Section 3.4).

It is important to note that variation in broadband availability across and within countries stemming from the technological features described above was especially pronounced in the initial phase of extensive broadband diffusion in the early 2000s and stems from the extensive (access) rather than the intensive (speed/bandwidth) margin.[31] Over time, many countries engaged in expanding ICT infrastructure to their so-called white spots, which are predominantly rural municipalities that would remain underprovided if left to market forces. Today, in most countries a basic provision of broadband Internet for almost all households has been achieved, and governments are aiming at ensuring speeds of up to 100 Mbit/s. Moreover, new technologies such as mobile broadband infrastructure emerged in recent years, attenuating the importance DSL to access the Internet.[32]

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 in countries with a farther-reaching voice-telephony network in 1996 (i.e., before the introduction of broadband Internet in any country[33]), individuals had on average earlier and greater access to broadband Internet, thus leading to the accumulation of ICT skills through learning-by-doing. 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:[34]

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

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:

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

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 Portal and ITU providing the number of broadband subscribers per inhabitant in the 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.[35] 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 pre-existing 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 pre-existing voice-telephony network does not capture actual broadband penetration well. In Korea, the government heavily subsidized the development of ICT infrastructure, 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 (Guellec and Wunsch-Vincent, 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.

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 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.[36] 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 (Roeller 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.[37] 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).[38] 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.

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 39.4 points, while the between-country standard deviation is just 8.2 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-maximising telecommunication carriers, which are, in turn, influenced by demand factors such as income level, educational attainment, and degree of urbanisation. 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.[39] 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.[40] 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 that increased with the length of the bypass, certain West German municipalities were excluded from early broadband Internet access.[41]

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 assigned MDF and merge this information, as well as information on the technological availability of DSL, with the German PIAAC data.[42] 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. The first-stage model in the within-country analysis is therefore a municipality-level version of Equation (4) using as instrument for individual ICT skills a dummy variable that indicates whether a municipality is more than 4 200 meters away from its assigned MDF.

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

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. Unfortunately, data on GDP per capita in 1999, the year before broadband introduction in Germany, are not available at the municipality level, so we instead use the municipality level unemployment rate and the local age structure, both measured in 1999, to control for the economic situation in a municipality before the emergence of broadband.[43]

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

3.5 Sample

Since the instruments described in Sections 3.3 and 3.4 reflect the technically determined availability of broadband Internet in a country in the first decade of the 2000s, they should primarily affect the ICT skills of individuals who most likely used the Internet during this decade. We now investigate whether the data are consistent with this assertion, which would also provide a rationale for excluding certain subgroups of the population from the sample. The discussion focuses on the cross-country specification, which is better suited for a subsample analysis than the within-country model due to substantially larger sample size. However, the results pattern is generally very similar in the within-country analysis.

First, we assess the relationship between ICT skills and traditional fixed-line diffusion by migration status. While natives and second-generation immigrants most likely have lived in the PIAAC test country during the first 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% 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 non-existent for first-generation immigrants. Table 1 shows the expected positive first-stage relationship for natives and second-generation immigrants (Columns (1) and (2)).[45] For first-generation immigrants, however, fixed-line diffusion and ICT skills are not significantly related (Column (3)).[46] 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.

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 more strongly affected by pre-existing fixed-line networks than age groups beyond the age of 49. We also observe a sharp decline in the effect of our instrument for individuals aged 16–19 years, who are likely to use technology other than DSL to access the Internet (e.g. mobile broadband on smartphones). These results provide a rationale for restricting our main estimation sample to 20–49 year-olds.[47]

4. Assessing the Identification Strategy

4.1 Cross-Country Instrumental-Variable Model

In Section 3.5, we showed 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. We now challenge the validity of our identification strategy in several other ways, providing further evidence that the instrument is unrelated to pre-existing factors that may also influence today's wages and, furthermore, that it does not just pick up an individual's general ability.

Although our IV strategy addresses potential concerns about measurement error and reverse causality, we might still worry that countries with better-developed voice-telephony networks before broadband rollout were also different in other characteristics that affect today's wages. To mitigate this concern, Table 2 presents the results from country-level first-stage regressions where ICT skills are replaced by various pre-broadband outcomes potentially relevant for today's wages. In Columns (1)–(8), we consider the following categories of pre-broadband variables: economic (i.e., hourly wages, wage growth between 1996 and 2012, years of schooling, and population size), general technology affinity (i.e., share of high-tech exports and share of STEM graduates), specialisation on ICT products (i.e., ICT goods trade as a share of total trade), and, to account for competition effects, other broadband-access infrastructure (i.e., the spread of cable TV networks).[48] 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 (Column (9)).

Importantly, to interpret the IV results in Section 5 as showing a causal effect of ICT skills on wages (vis-à-vis a general ability effect), the spread of pre-existing voice-telephony networks has to insulate 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 3 shows the results of these placebo tests. Conditional on ICT skills, we find that neither numeracy nor literacy skills are significantly related to the pre-existing fixed-line network, while the instrument continues to be a relevant predictor of ICT skills when the other skill domains are accounted for.[49] These results indicate that our instrument captures the "right" variation and provide confidence that the returns-to-ICT-skills estimates discussed below are not biased due to unobserved skills of the PIAAC respondents.[50]

Since our instrument relies on between-country variation, our first-stage relationship may be driven by some country outliers. 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, and no country stands out as particularly important in terms of our identifying association.[51]

Finally, the learning-by-doing mechanism in the accumulation of ICT skills should operate not only at the intensive margin of ICT skills, but also at the extensive margin. Thus, countries with a better-developed voice-telephony network before the emergence of broadband should have more individuals with at least basic ICT competencies, because the higher broadband penetration in these countries facilitated the development of ICT skills. We investigate these extensive-margin effects of the instrument using as outcome a binary variable that takes the value 1 if a respondent has a valid ICT test score and 0 otherwise; respondents with missing ICT test scores lack basic computer skills needed to undertake an assessment on a computer or opted out from the computer-based test (see Section 2).[52] Columns (1)–(3) in Table A-3 show that pre-existing fixed-line diffusion is indeed a significant predictor of basic ICT literacy.[53] Since the intensive-margin effects of the pre-existing fixed-line diffusion are in the focus of the paper, Columns (4)–(6) present specifications analogous to those in Columns (1)–(3) with the indicator of ICT literacy replaced by the level of ICT skills (equivalent to our first-stage model in Equation (4)). Corroborating the above results, initial ICT infrastructure is strongly associated with the level of ICT skills also when individual-level variables are included successively.

4.2 Within-Country Instrumental-Variable Model

In our within-country IV model, one of the key threats to identification is that people selectively relocated from dwellings at a distance to the MDF above the 4 200-meter threshold to dwellings below the threshold. To assess the relevance of this concern empirically, we first draw on data from the German regional statistics that contain information for the universe of West German municipalities ($n > 8000$) in the period 2001–2012.[54] We calculate the annual out-migration rate for each municipality as the number of inhabitants moving out of a municipality in a given year relative to the municipality's total population.[55] Using a pooled regression with only year dummies and a threshold indicator as regressors, we find that the average out-migration rate between 2001 and 2012 is 5.9% in municipalities below the threshold.[56] The coefficient on the threshold dummy is very small at –0.07 percentage points and even negative, implying an out-migration rate in above-threshold municipalities of 5.8%. Due to the large sample size, the threshold coefficient is even statistically significant at the 10% level. Regressions for each individual year show that the threshold coefficient is always negligible in economic terms, being statistically significant only in the years 2001–2004. Thus, results consistently show that people are not systematically leaving areas where broadband Internet is technologically not available.

We complement this municipality-level analysis by employing annual household survey data from the German Socio-Economic Panel (SOEP), which allow us to identify moves at a very granular regional level (including moves within the same neighbourhood) (Wagner, Frick, and Schupp 2007). We use the exact geo-coordinates of the SOEP households in West Germany for the survey waves 2000–2010 to calculate whether a household has changed its distance to the MDF between two survey waves.[57] 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%) 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% (6.2%) for households from dwellings situated below (above) the threshold; the difference between both location rates is not statistically significant. Thus, corroborating the results from the municipality-level analysis, the average relocation rate of above-threshold households is again somewhat *lower* than that of below-threshold households. Furthermore, 93.8% of the relocations do not involve a crossing of the threshold.

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

We also need to ensure that our within-country specification insulates the effect of ICT skills on wages from the effect of general ability, as we have shown for the cross-country sample in Table 3. Table 4 presents the analogous placebo tests for the within-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 has the expected negative sign even conditional on the other skill domains. The result that broadband availability does not increase skills in general is also in line with the findings of Faber, Sanchis-Guarner and Weinhardt (2015). Using a boundary-discontinuities strategy in the U.K. that relies on a similar idea as our within-country model, they find that the availability of fast Internet at students' homes has no effect on their test scores.

Although based on a small sample of only 96 respondents without basic ICT competencies, exogenous broadband availability can also explain the extensive-margin effects of ICT skills across German municipalities. Individuals in municipalities above the 4 200-meter threshold have a 7.5 percentage points lower probability of having a non-missing ICT test score, reflecting at least basic ICT literacy (results are available upon request).

5. Returns to ICT Skills

5.1 Cross-Country Evidence

Baseline estimates. After providing a careful analysis of the validity of our identification strategy, we now estimate the causal effect of ICT skills on individuals' wages. Table 5 presents the results from our cross-country IV model. 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. In Columns (1)–(3), ICT skills are measured at the individual level representing our preferred specification. For comparison, Columns (4)–(6) present analogous models with ICT skills aggregated at the country level, since we effectively use only variation in ICT skills across countries due to the country-level instrument.[58]

In the lower panel of Table 5, we report the first-stage coefficient on pre-existing fixed-line diffusion and the F-statistic on the excluded instrument. In line with the evidence presented in Section 3.5, the instrument turns out to be a strong predictor of ICT skills. In the most demanding specification with all control variables (Column (3)), the F-statistic is 52.0. The first-stage estimate suggests that increasing the voice-telephony penetration rate from 0 to 100% is associated with an increase in ICT skills of about 11.3 country-level standard deviations (96 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% (Poland) and 68% (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 48 points.[59]

The second stage in the upper panel of Table 5 shows the effect on wages of an increase in ICT skills induced by pre-existing fixed-line networks. Across specifications, our results indicate significant returns to ICT skills. In the specification with all controls in Column (3), the ICT-skill coefficient of 0.079 implies that a one-standard-deviation increase in ICT skills attributable to a historically larger fixed-line network leads to a 7.9% increase in wages. While all the individual-level control variables enter the regressions with the expected sign[60], 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.[61] Results are very similar when using country-level aggregates of ICT skills instead of individual-level skills, shown in Columns (4)–(6).[62]

As a benchmark to assess the magnitude of the estimated effect, 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 roughly equals 40% of the learning progress of school-attending-PIAAC respondents between lower secondary and upper secondary education, which amounts to 20 PIAAC points across the countries participating in the study.[63] In terms of magnitude, our estimated returns to ICT skills are close to the well-identified estimates on the returns to one additional year of schooling in developed countries.[64] It is also useful to compare the returns to ICT skills with existing estimates on the returns to cognitive skills in other domains. In their sample of prime-age, full-time employed workers, Hanushek, Schwerdt, Wiederhold, and Woessmann (2015) find returns to numeracy skills of 10.2% in a specification analogous to ours (see pooled model in their Table 4); returns are very similar for literacy skills.[65] 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 labour market than more traditional cognitive skills.[66]

Given our identification story, the IV approach reflects the following three-stage model: (1) fixed-line diffusion in 1996 predicts broadband Internet diffusion until 2012; (2) broadband Internet diffusion predicts ICT skills; and (3) ICT skills predict wages. To show that the expected relationship holds at each stage, we estimate a recursive system of three equations using a seemingly unrelated regressions model. Results shown in Table A-5 indicate that pre-existing fixed-line diffusion is positively associated with broadband diffusion in 2012 (first equation) and that broadband diffusion is positively related to ICT skills (second equation), which significantly predict wages (third equation). Strikingly, the estimated returns to ICT skills in these models are very similar to the IV estimation results in Table 5.[67]

Effect heterogeneity In Table 6, we trace through the returns to ICT skills in various worker subgroups. On the one hand, these subsample analyses show whether the estimated average returns are a good depiction of the value of ICT skills in a variety of subgroups that are frequently singled out as facing different labour-market challenges. On the other hand, these analyses address the concern that the extent of the pre-existing fixed-line network may just pick up factors at the country level that influence individuals' wages. If this was indeed the case, we would not expect to find differences in the returns across worker groups.

Probably the most direct test whether our estimates reflect returns to ICT skills vis-à-vis the wage effects of some unobserved country factors is to estimate returns 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.[68] 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 non-existent there. The estimation results in Column (2) substantiate this conjecture: the coefficient on ICT skills is small and statistically insignificant in a sample of workers in elementary occupations.[69] We array these returns with those occurring in managerial occupations, which rely most heavily on computers to perform the required tasks at work. As expected, returns to ICT skills for managers are above the baseline returns and even exceed 10% (Column 3).[70] Second, in Columns (4) and (5), we observe that ICT skills are less strongly rewarded in the public sector than in the private sector (3.3% vs. 9.7%), which is in line with the seniority-based and rather compressed pay scale in the public sector. Third, estimated returns are higher for men (9.8%) than for women (6.5%), but the difference is not statistically significant (Columns (6) and (7)). Fourth, when dividing the sample in "young" and "old" workers using the midpoint of our age distribution (i.e., 35 years) as cut-off, returns to ICT skills turn out to be higher for young workers (9.0%) than for old workers, but even the latter have returns of 6.5% (Columns (8) and (9)).[71]

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. 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, and are also robust to excluding Korea, where the government heavily subsidized the rollout of fiber to homes. Specifications that restrict the analysis to European countries only or that include continental fixed effects also yield very similar results as the baseline model (results available upon request).

Specification checks. In Tables A-9 and A-10, we present a series of robustness checks designed to test the sensitivity of our main results to adding further controls at the country level or the individual level. If our identification strategy addresses omitted-variable bias in the estimation of skill returns, adding further variables that are important for wage determination should leave the estimated IV-coefficient on ICT skills unaffected.

In Table A-9, we add control variables characterising the labour market, namely, union density, employment protection legislation, 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 that completed tertiary education. We also add the current cell phone diffusion to proxy for Internet access technologies other than DSL.[72] In Table A-10, we perform a similar exercise with additional individual-level controls, namely, a full-time employment indicator, parental education, and self-assessed health status.

Reassuringly, the estimated returns to ICT skills remain very similar when including these additional controls, providing evidence that our IV strategy indeed identifies variation in ICT skills that is independent of potentially omitted variables at the country or individual level.[73]

5.2 Within-Country Evidence

Baseline estimates. 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. 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 assigned 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 65% 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. Although we do not find evidence that the mobility pattern is systematically related to our instrument (see Section 4.2), it is a source of measurement error leading to an attenuation bias in the first-stage regression. To address a potential weak-instrument problem (e.g. Bound, Jaeger, and Baker 1995), we use LIML to obtain our IV estimates since LIML minimizes the coefficient estimate bias associated with weak instruments.[74]

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 15.2% in the full sample (Column (3)). Estimated returns to skills are 17.4% in the restricted sample, just shy of statistical significance ($p = 0.117$) (Column (6)). The returns are almost twice as large as 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.[75]

The three-equation estimations in Table A-11 indicate that the 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 5 percentage points lower broadband availability (4.2 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.[76]

Specification checks. Table A-12 provides estimates for West Germany based on regressions analogous to those underlying Table A-10. For brevity, we report only sensitivity checks for the full sample, but we find qualitatively similar results in the no own MDF sample. Across specifications, we again observe that the coefficient on ICT skills changes very little compared to the baseline estimate.[77]

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 non-routine abstract tasks, which require ICT skills.[78] In particular, Autor, Levy, and Murnane (2003) relate changes in the U.S. labour structure since the 1960s to the proliferation of computers in the workplace.[79] The authors ask what kind of tasks computers execute that substitute for or complement tasks performed by workers. Therefore, instead of using conventional labour 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 labour. The basic idea is that computers substitute for routine tasks (those that can be accomplished by following explicit rules) and are complementary to non-routine abstract tasks (such as problem solving and coordination).[80] The underlying reasoning is that routine tasks embody explicit knowledge that can be relatively easily programmed, which is not the case for non-routine tasks. Moreover, an increase in the supply of codifiable tasks increases the marginal productivity of employees who engage extensively in non-routine tasks and who use routine work output as their work input.[81]

Trends toward a rising importance of abstract tasks may be a potential mechanism behind our result that ICT skills are considerably rewarded in modern labour markets. If high ICT skills are required to obtain jobs that are pervasive in abstract tasks because these tasks are complementary to computers, any wage premium abstract jobs pay would imply positive returns to ICT skills. We therefore compare the ICT skills of workers in occupations that make intense use of abstract tasks with the ICT skills of workers with little abstract task intensity, using the population median to distinguish between jobs with high versus low task intensity.[82] 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).[83]

Figure 6 shows the results from this analysis. We observe in Panel A that workers in jobs with a high abstract task content 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 jobs' task content when looking at the index of computer use at work introduced in the analysis of effect heterogeneity in Section 5.1. Computer use by workers in occupations requiring high abstract tasks is 35% of a standard deviation above the global mean and is 44% 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.[84]

Although being purely descriptive, the results in Figure 6 have two important implications: First, they support the idea that the upsurge of personal computers in recent decades complements workers in executing non-routine abstract tasks, and substitutes for workers performing routine and manual tasks. This reinforces the conclusions in Autor, Levy, and Murnane (2003) with individual-level data on computer use at work. Second, our findings suggest that the proliferation of computers is potentially a mechanism behind the positive returns to ICT skills in modern labour markets. Jobs that are dominated by abstract tasks pay substantial wage premiums[85] and having high ICT skills seems to be a necessary prerequisite to enter these well-paid jobs.

7. Conclusion

This paper investigates the labour-market returns to ICT skills using a novel dataset that contains direct measures of individuals' ICT skills in 19 developed economies. We identify exogenous variation in ICT skills by exploiting technological peculiarities that determine broadband Internet availability across countries and across German municipalities, respectively. The underlying idea is that ICT skills are developed through learning-by-doing, which is facilitated when having access to the Internet. Our results indicate that better ICT skills are systematically related to higher wages: a one-standard-deviation increase in ICT skills leads to an almost 8% increase in wages in the international analysis and to an increase of 15% in the German analysis. Placebo tests showing that the variables which exogenously determine Internet access cannot explain any variation in numeracy or literacy skills suggest that our IV models are able to insulate the wage effect of ICT skills from that of general ability.

By showing that ICT skills are rewarded quite substantially in the labour market, our results support Neelie Kroes' notion of ICT skills as "the new literacy." Still, our findings do not provide conclusive evidence how modern knowledge-based economies value ICT skills relative to other types of skills because sources of exogenous variation in these other skills are lacking. 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 United States are 16 and 11 percentage points less likely to have an Internet connection than white households, respectively (CEA, 2015). This digital divide may have important implications for the future labour-market participation of the disadvantaged groups because structural and technological change will likely raise the demand for expertise in performing ICT-related tasks.[86] The fundamental insight of this paper that the skills to master digital technologies can be promoted by providing access to ICT infrastructure suggests that the efforts by policy-makers worldwide to expand broadband Internet access may prevent a drifting apart in employment opportunities when advances in ICT change job demands.

Notes

[1] www.getonlineweek.eu/vice-president-neelie-kroes-says-digital-literacy-and-e-skills-are-the-new-literacy/, (accessed 13 January, 2016).

[2] PIAAC assessed a domain of skill described as ‘problem solving in technology-rich environments’ that covered “the abilities to solve problems for personal, work and civic purposes by setting up appropriate goals and plans, and accessing and making use of information through computers and computer networks” OECD (2012). In this paper, when discussing the results from PIAAC, the term ‘ICT skills’ is used (among other things) as a convenient shorthand to refer to the skills measured by the assessment of ‘problem solving in technology-rich environments’.

[3] 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 behaviour; 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.

[4] Other studies have used variation in technological broadband availability across locations as a source of exogenous variation in actual use (e.g. 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 stemming from limited funding of a public program and not due to the decisions of profit-maximising telecommunication carriers.

[5] Our result that exogenous Internet availability affects only a specific set of skills is in line with Malamud and Pop-Eleches (2011), 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), Acemoglu and Autor (2011), Firpo, Fortin, and Lemieux (2011), Autor and Dorn (2013), Goos, Manning, and Salomons (2014), Akerman, Gaarder, and Mogstad (2015), and related earlier work by Acemoglu (1998) and Bresnahan, Brynjolfsson, and Hitt (2002).

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

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

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

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

[11] The countries that participated in PIAAC are Australia, Austria, Belgium (Flanders), Canada, Cyprus (see footnote 19), 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.

[12] The PIAAC Public Use File reports hourly wages for Austria, Canada, Germany, Sweden, and the United States only as a worker’s decile rank in the country-specific wage distribution. For Germany, we obtained the Scientific Use File, which contains continuous wage information. For the remaining countries, we follow Hanushek, 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% of the wage distribution to limit the influence of outliers.

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

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

[15] *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.

[16] See OECD (2013, p. 89) and OECD (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.

[17] 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 Rammstedt (2013) and OECD (2015).

[18] 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 we impute missing ICT skills using questions for assessing numeracy skills. For this we regress ICT skills on numeracy questions that were asked in the same way in both the paper-based and computer-based mode (1=right answer; 0=wrong answer). For each country individually, we then multiply the estimated coefficients with an indicator that equals 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.

[19] Note by Turkey: The information in this document with reference to "Cyprus" relates to the southern part of the Island. There is no single authority representing both Turkish and Greek Cypriot people on the Island. Turkey recognises the Turkish Republic of Northern Cyprus (TRNC). Until a lasting and equitable solution is found within the context of the United Nations, Turkey shall preserve its position concerning the "Cyprus issue".

Note by all the European Union Member States of the OECD and the European Union: The Republic of Cyprus is recognised by all members of the United Nations with the exception of Turkey. The information in this document relates to the area under the effective control of the Government of the Republic of Cyprus.

[20] 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.

[21] The international PIAAC sample with 24 countries contains 164 997 observations. Without the four countries that opted out from the ICT skills assessment and the Russian Federation, sample size is 138 383 observations. ICT skills could not be measured for 32 831 individuals. We restrict the sample to persons who are employed at the time of the PIAAC survey, trim the bottom and top 1% of the wage distribution, and exclude self-employed who do not report hourly wage information in PIAAC, leading to a decrease in sample size by 41 549 observations. The age restriction

further reduces the sample by 17 913 workers and dropping first-generation immigrants by 4 876 workers. Finally, we exclude 544 workers with missing information on migration status, gender, work experience, or years of schooling.

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

[23] 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.

[24] 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.

[25] 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 8.2 points on the PIAAC scale; a municipality-level standard deviation is 20.6 PIAAC points.

[26] 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).

[27] 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.

[28] 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.

[29] The major alternative fixed-line access technology is broadband access via cable TV networks.

[30] In the United Kingdom, the MDF is usually referred to as "Local Exchange"; in the United States, it is called "Central Office."

[31] In the early phase of its diffusion, 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.

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

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

[34] Note that in Czernich et al. (2011) this maximum reach of broadband is also determined by the spread of the cable TV network before broadband was introduced, as this infrastructure can be used for broadband rollout as well. However, we do not use the extent of the pre-existing cable TV network to instrument for ICT skills because we expect a considerably weaker association due to a direct "distraction effect." For instance, data from American Time Use Survey reveal that in 2003 the average American spent 2.58 hours per day in front of the TV but only spent 0.08 hours per day on the phone. Therefore, the distraction effect of the cable TV network is far higher than that of voice telephony. In line with this reasoning, we find no significant relationship between the size of the cable TV networks in 1996 and ICT skills in PIAAC (results available upon request). Since the extent of pre-existing cable TV networks is neither correlated with the diffusion of voice-telephony networks in a country (see Table 2), competition from cable TV networks is unlikely to be a threat to our identification strategy.

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

[36] 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 3.5). 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 labour-force participation rates.

[37] 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 labour relations.

[38] 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% of U.S. counties. Interestingly, these counties were already well-performing before high-speed Internet diffusion took off.

[39] 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). Berlin is also dropped from the analysis because we are unable to distinguish between former West and East Berlin in terms of DSL availability.

[40] 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.

[41] 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).

[42] 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.

[43] Data come from the German Federal Statistical Office. The unemployment rate is calculated by dividing the number of unemployed individuals by the population aged 18 to 65 years. To account for territorial changes due to

municipality reforms that took place between 1999 and 2012, we use population weights provided by the Federal Institute for Research on Building, Urban Affairs, and Spatial Development to recode the data in *ArcGIS*.

[44] Recent research has shown that clustered standard errors can be biased downward in samples with a small number of clusters (e.g. Donald and Lang, 2007; Cameron, Gelbach, and Miller, 2008; Angrist and Pischke, 2009; Ibragimov and Muller, 2010; Imbens and Kolesar, 2012). Although there is no widely accepted threshold when the number of clusters is "small", the work of Cameron, Gelbach and Miller (2008), Angrist and Pischke (2009), and Harden (2011) suggests a cut-off 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.

[45] See Section 5.1 for a discussion of effect size.

[46] 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 immigrant types.

[47] In Section 5.1, we show that our estimation results also hold for other age ranges.

[48] 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.

[49] 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. Since this positive correlation vanishes once we include ICT skills, pre-existing fixed-line diffusion affects numeracy and literacy skills only through ICT skills.

[50] Note that we refrain from controlling for numeracy or literacy skills in the IV regressions because cognitive skills in PIAAC are measured simultaneously with wages and are thus likely endogenous. Instead, we prefer to use years of schooling to proxy for a person's level of human capital, which is determined before labour-market entry. However, returns-to-ICT-skills estimates are very similar when we replace years of schooling by numeracy or literacy skills.

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

[52] In our sample of workers aged 20–49 years without first-generation immigrants, the share of persons with missing ICT skills is only half as large as in the full sample (12% vs. 24%). Thus, restricting the sample to young workers without a strong migration background somewhat alleviates the problem of missing ICT test scores. However, even in this sample there is considerable heterogeneity across countries in the share of ICT illiterates. Three countries have shares of ICT illiterates larger than 20%: Poland (34%), Japan (24%), and the Slovak Republic (23%). These high shares differ noticeably from those in another set of four countries with shares of ICT illiterates below 5%: Sweden (2.5%), Netherlands (3.3%), Norway (3.9%), and Finland (4.6%).

[53] Results are very similar if we follow OECD (2015) in adding respondents with very low ICT skills to the group of persons without basic ICT skills.

[54] Broadband was introduced in Germany in 2000.

[55] We exclude the year 2006 from the analyses because complete municipality data were unavailable for this year. We use *ArcGIS* to account for territorial changes between 2001 and 2012.

[56] The threshold dummy is binary variable taking the value 1 if a municipality is above the 4 200-meter threshold and 0 otherwise.

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

[58] To account for demographic effects and for country differences in pre-broadband economic development and current wages, country-level ICT skills are cleaned of all control variables included in Table 5.

[59] Columns (4)–(6) in Table A-3 report all first-stage coefficients for the corresponding specifications in Table 5, Columns (1)–(3). 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. Due to positively sloped age-earnings profiles, the negative correlation between ICT skills and the average wages of the elderly workforce (who typically have relatively low ICT skills) is also plausible.

[60] The coefficient on GDP per capita has the expected positive sign without the wage control.

[61] The corresponding OLS specifications are presented in Table A-4. The estimated returns to skills in the OLS models tend to be somewhat larger than in IV, but OLS and IV estimates are very similar in the specification with all controls. Importantly, Column (4) of Table A-4 shows that returns to skills are very similar when including country fixed effects, which indicates that the country-level control variables capture the most relevant level differences in wages across countries.

[62] Results are robust to aggregating all variables to the country level. OLS results of cross-country regressions (with and without control variables) are plotted in Figure A-2.

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

[64] To estimate a causal effect of education on earnings, these studies use variation in education stemming from changes in compulsory schooling laws and in restrictions on child labour, variation in education stemming from differences in the distance to the nearest educational institution, and variation in education occurring between siblings and twins. See Angrist and Krueger (1991) for an early example of using compulsory schooling laws to identify exogenous variation in educational attainment and Card (1999), Heckman, Lochner, and Todd (2006), and Woessmann (forthcoming) for reviews.

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

[66] While the estimates in Table 5 are to be interpreted as individual (or private) returns to ICT skills, the value of skills to society may exceed the private return because of positive social returns due to human capital externalities from a high-skilled labour force. Unfortunately, we cannot assess whether social returns to ICT skills exist because this would require to instrument for both individual-level and aggregate ICT skills (see the discussion in Acemoglu and Angrist, 1999).

[67] Columns (1)–(3) in Table A-6 show the reduced-form estimates for the international analysis corresponding to Columns (1)–(3) in Table 5. Consistent with the intuition of our identification strategy, we observe that countries with larger voice-telephony networks in 1996 pay significantly higher wages today.

[68] 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. All calculations are performed for each country individually to account for possible differences in answering behaviour.

[69] This result cannot be explained by (i) a weak instrument—the first-stage F-statistics is 21.9 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.

[70] To investigate whether returns to ICT skills are significantly different between subgroups, we added interaction terms of the subgroup indicators with the ICT skill measure (and with all control variables) to our baseline model. In this fully interacted IV model, we instrument for the interaction of the subgroup indicator and ICT skills by interacting the indicator with fixed-line diffusion in 1996. Table A-7 presents the results. We observe that returns to ICT skills in elementary occupations are significantly smaller than returns in managerial occupations. (In unreported analysis, we find that returns in elementary occupations are also smaller than those in all other occupations.) In the interaction model, we can pursue an even more rigorous approach and include country fixed effects instead of country-level control variables. Identification in this model comes only from variation within countries, so all factors that determine wages at the country level (e.g. labour-market institutions, economic policy, social norms, and political stability) are also taken into account. Since the instrument (past fixed-line diffusion) is absorbed by the fixed effect, we estimate the model without including ICT skills linearly. Even in this quite demanding specification, shown in Columns (5)–(8) in Table A-7, the results on the interactions of returns to skill with the subgroup indicators remain intact and are in fact very similar to those without country fixed effects. This again suggests that the country-level controls included in the baseline model account for relevant differences in wages across countries.

[71] Although returns to ICT skills tend to decrease with age, we also find significant returns in a more encompassing sample that also includes persons aged 50–65 years. Results are qualitatively similar for other age groups. See Table A-8 for details.

[72] 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.

[73] Unreported regressions show that returns to ICT skills do not change 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. Data on gross fixed capital formation are provided by the OECD and data on (ICT) patents are provided by Eurostat.

[74] We also construct the Anderson and Rubin (AR) 95% 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 upon request.

[75] Large returns in Germany compared to other developed economies are consistent with other analysis that identifies the widening of the income distribution in Germany in recent years; see Dustmann, Ludsteck, and Schoenberg (2009) and Card, Heining and Kline (2013).

[76] In line with the negative first-stage relationship between the technical threshold in broadband availability and ICT skills, Columns (4)–(9) in Table A-6 show a significantly negative reduced-form influence on wages of the threshold instrument throughout.

[77] Due to the limited sample size, a subsample analysis does not appear to be meaningful in the West German sample. For instance, the sample includes only 58 (56) persons in elementary (managerial) occupations.

[78] A number of studies suggest that the skill structure of developed economies has changed remarkably since the second half of the 20th century. Skill upgrading was a prevalent trend and widespread evidence points toward increases in skill premiums (e.g. Autor, Katz, and Krueger, 1998; Acemoglu, 2003; Goldin and Katz, 2008) and in wage inequality (for recent evidence, see Autor, Katz, and Kearney, 2008; Dustmann, Ludsteck, and Schoenberg, 2009; Card, Heining, and Kline, 2013; Autor, 2014).

[79] See Handel (2007) for a critical appraisal of the role of computers for the growth in wage inequality in the United States.

[80] 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, the 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, 2008).

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

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

[83] They combine the five original DOT task measures of Autor, Levy, and Murnane (2003) into three task aggregates: (non-routine) abstract tasks, routine tasks, and (non-routine) manual tasks (see also Akerman, Gaarder, 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.

[84] 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.

[85] In our sample, jobs which are intensive in abstract tasks pay on average 25% 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.

[86] Alternative employment opportunities will mainly arise in low-paid, manual-intensive occupations that are difficult to automate but require limited formal education (e.g. janitors and cleaners, home health aides, and security personnel). See Autor and Dorn (2013) and Goos, Manning, and Salomons (2014) for recent evidence on this “job polarization” hypothesis, and Michaels, Natraj, and Van Reenen (2014) for an investigation of the role of ICT in the polarization of skill demand.

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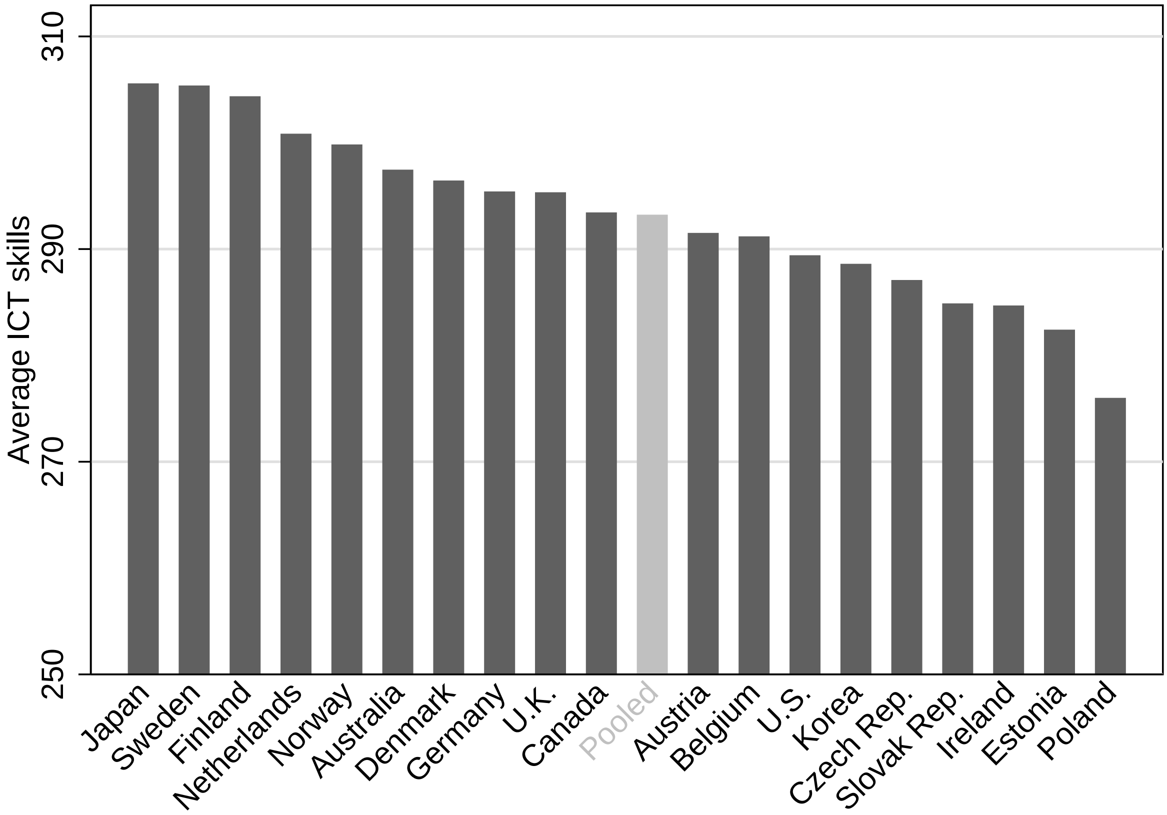
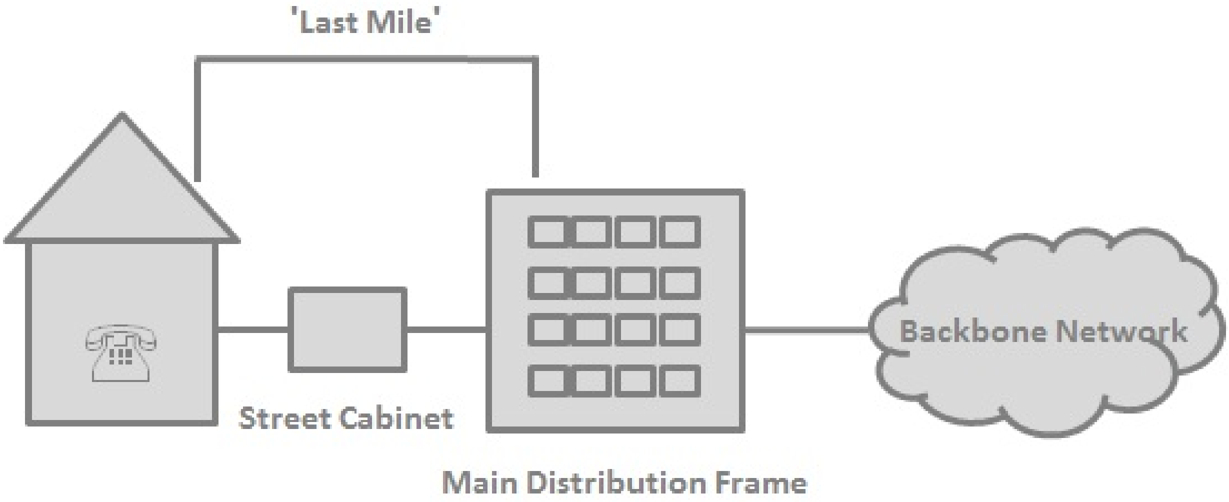
Figures and Tables

Figure 1: ICT Skills Around the World



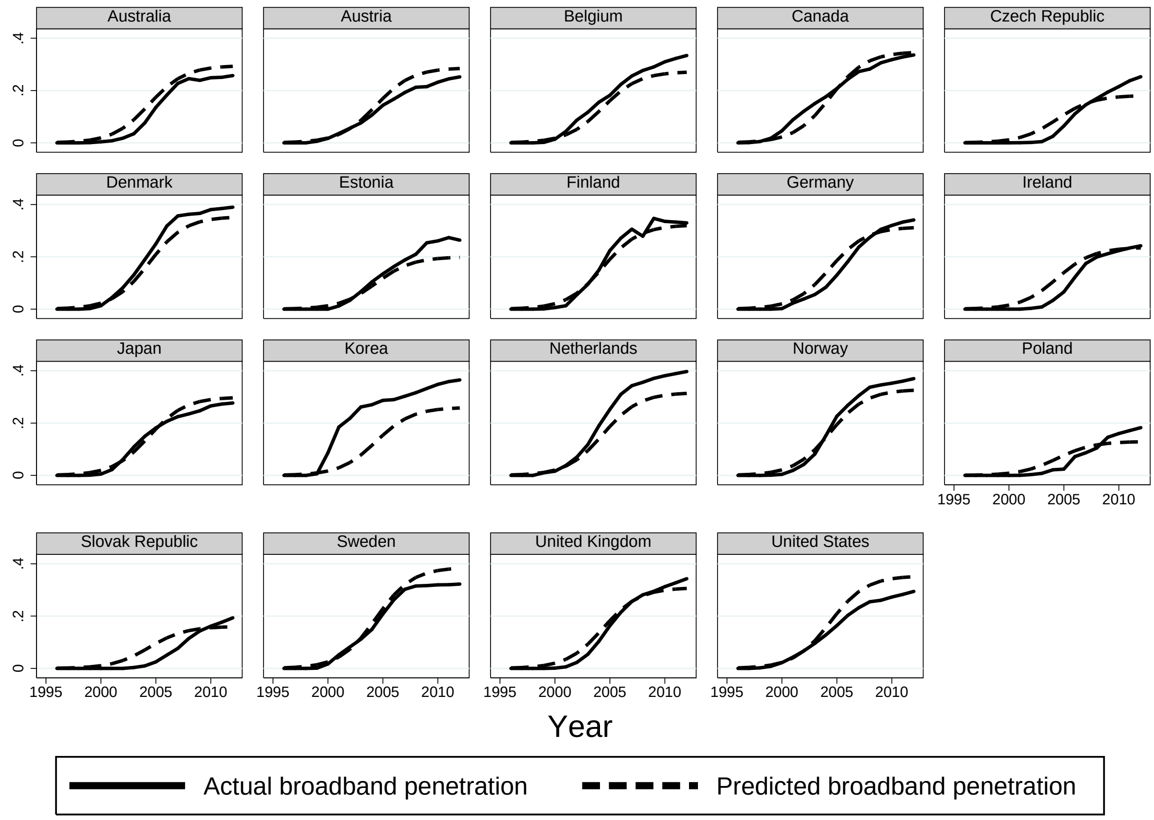
Notes: Average ICT skills across countries. Sample: employees aged 20–49 years, no first-generation immigrants. *Data source:* PIAAC (2012).

Figure 2: The Structure of a DSL Network



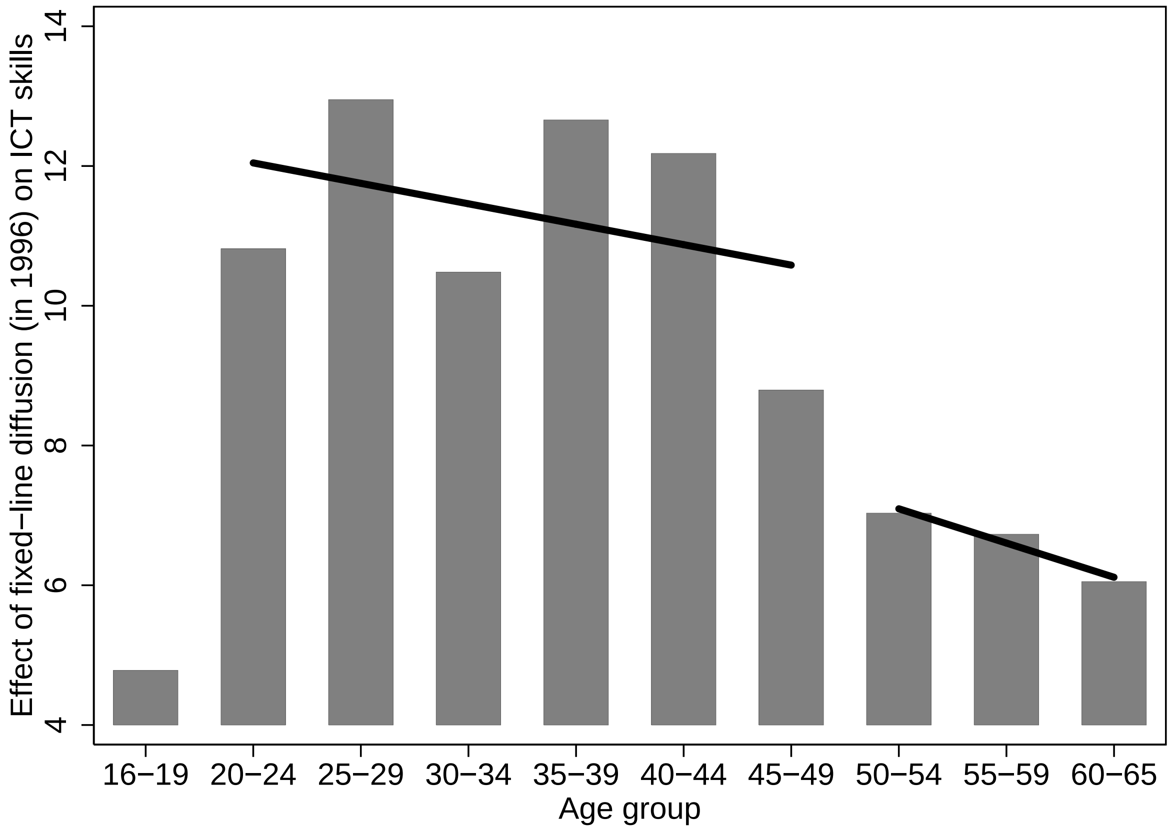
Notes: The figure shows the structure of a DSL network that relies on the "last mile" of the preexisting fixed-line voice-telephony network. The "last mile" consists of copper wires connecting every household via the street cabinet to the main distribution frame. At the main distribution frame, a DSLAM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

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



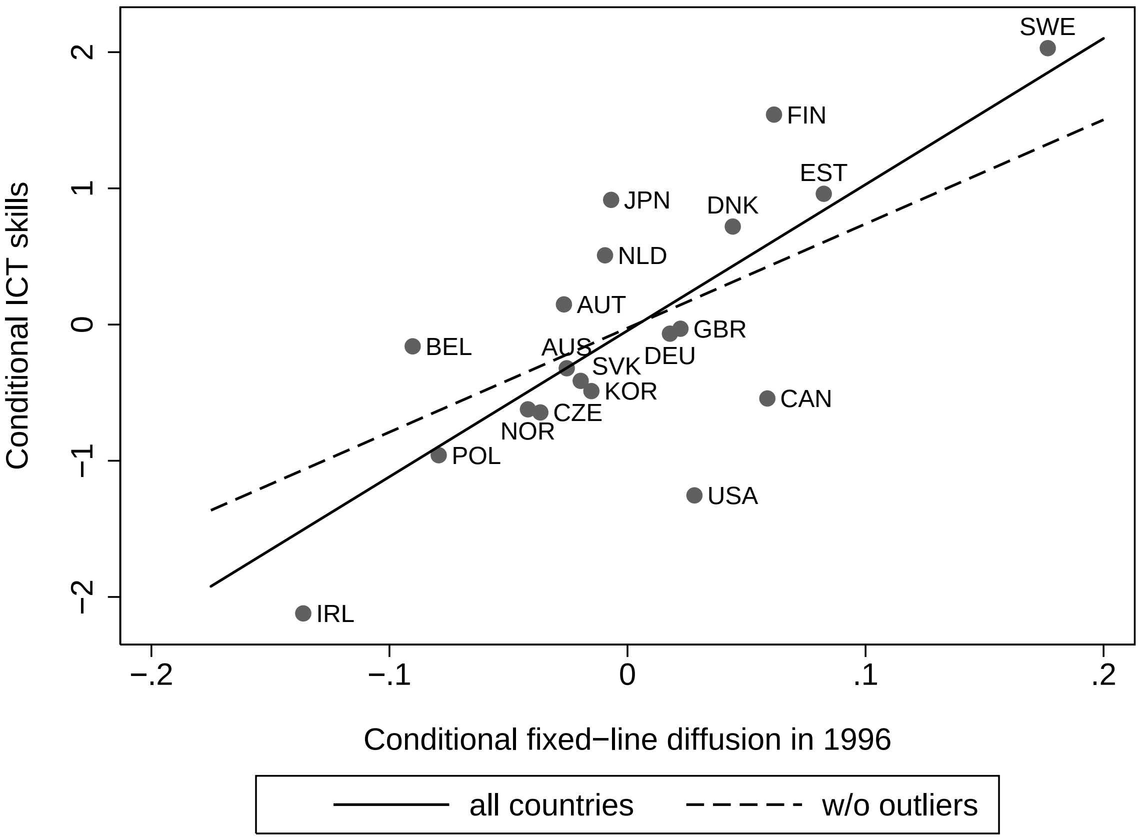
Notes: Actual broadband penetration is measured as the number of broadband subscribers per inhabitant in 2012. Predicted broadband diffusion is derived from nonlinear least squares estimation of a diffusion curve based on the voice-telephony penetration rate (telephone access lines per inhabitant) in 1996. See Section 3.3 for details. Data on broadband diffusion for Estonia available only from 2001 onward, assumed to be zero before. *Data sources:* ITU, OECD.

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



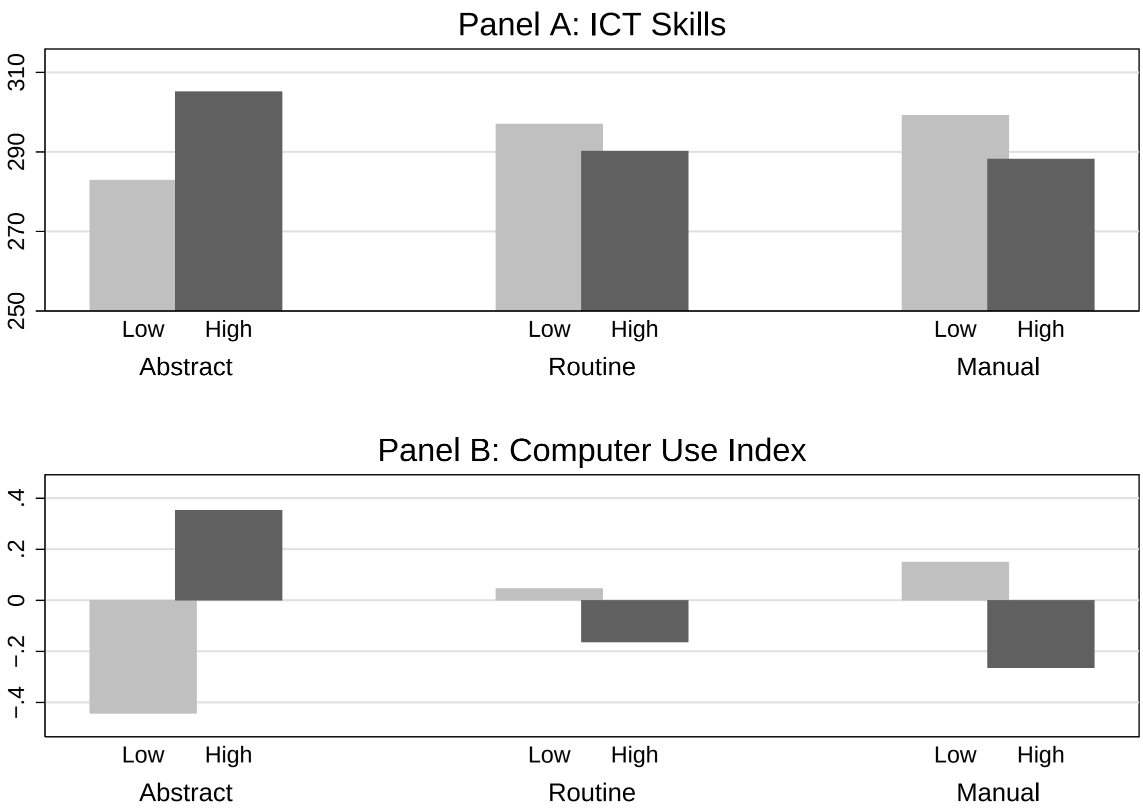
Notes: Coefficient estimates on fixed-line voice-telephony diffusion (in 1996) for indicated five-year age groups in a regression of ICT skills (standardized to std. dev. 1 across countries with the country-level std. dev. as "numeraire" scale) on fixed-line diffusion and all control variables included in Table 5, Column (3). 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 (2012).

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 5, Column (3). 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 (2012).

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 (2012).

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	11.684***	9.217***	–1.408
	(1.667)	(1.434)	(1.447)
GDP per capita in 1996 (log)	1.111*	0.871*	1.175
	(0.566)	(0.502)	(1.066)
Average wage level 50_59 (log)	–3.061***	–2.110***	–2.421**
	(0.660)	(0.571)	(0.941)
Experience	–0.072**	–0.057	–0.053
	(0.026)	(0.037)	(0.055)
Experience^2 (/100)	–0.096	–0.017	0.066
	(0.075)	(0.114)	(0.145)
Female	–0.917***	–0.681***	–0.877***
	(0.102)	(0.163)	(0.191)
Years of schooling	0.643***	0.680***	0.663***
	(0.026)	(0.031)	(0.043)
R squared (adjusted)	0.18	0.18	0.14
Individuals	36,671	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). *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 from the PIAAC microdata (i.e., wages are measured in 2011/2012). 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 (2012).

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	–0.305	0.005	0.976	0.046	–0.348	–0.020	0.089	0.508	6.115***
	(0.418)	(0.528)	(2.551)	(0.108)	(0.348)	(0.240)	(0.203)	(0.344)	(1.265)
GDP per capita in 1996 (log)	0.258	–0.107	1.048	0.049	–0.103	–0.103	–0.069	–0.277*	0.910
	(0.230)	(0.221)	(1.420)	(0.050)	(0.095)	(0.078)	(0.208)	(0.141)	(0.607)
Average wage level 50_59 (log)	0.912***	–0.193	–1.143	–0.032	0.379**	0.160	–0.055	0.161	–1.170**
	(0.206)	(0.247)	(1.243)	(0.044)	(0.159)	(0.106)	(0.080)	(0.112)	(0.430)
R squared	0.90	0.37	0.05	0.10	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). *GDP per capita in 1996 (log)* is measured in PPP-USD. *Average wage level 50_59 (log)* is the mean wage in 2011/2012 (in PPP-USD) of employees aged 50–59 years. 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 (2012), World Bank.

Table 3: Cross-Country Placebo Test

Dependent variable: cognitive skills in	Numeracy	Literacy	ICT	ICT
	(1)	(2)	(3)	(4)
Fixed-line diffusion in 1996	1.796	2.148	4.339***	3.501***
	(1.829)	(1.245)	(0.899)	(0.592)
ICT skills	0.556***	0.662***		
	(0.018)	(0.018)		
Numeracy skills			0.860***	
			(0.017)	
Literacy skills				0.809***
				(0.014)
Country characteristics	X	X	X	X
Individual characteristics	X	X	X	X
R squared (adjusted)	0.57	0.62	0.57	0.62
Individuals	40,670	40,670	40,670	40,670
Countries	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). 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 (2012).

Table 4: Within-Country Placebo Test

	Panel A: Full Sample			
Dependent variable: cognitive skills in				
	Numeracy	Literacy	ICT	ICT
	(1)	(2)	(3)	(4)
Threshold	0.308**	0.052	–0.549***	–0.341***
	(0.121)	(0.170)	(0.099)	(0.123)
ICT skills	0.705***	0.735***		
	(0.026)	(0.024)		
Numeracy skills			0.679***	
			(0.021)	
Literacy skills				0.728***
				(0.021)
Municipality characteristics	X	X	X	X
Individual characteristics	X	X	X	X
R squared (adjusted)	0.61	0.65	0.58	0.62
Individuals	1,391	1,391	1,391	1,391
Municipalities	204	204	204	204

	Panel B: No Own MDF Sample			
Dependent variable: cognitive skills in				
	Numeracy	Literacy	ICT	ICT
	(1)	(2)	(3)	(4)
Threshold	0.201	0.138	–0.631***	–0.479***
	(0.166)	(0.159)	(0.218)	(0.138)
ICT skills	0.603***	0.713***		
	(0.067)	(0.073)		
Numeracy skills			0.668***	
			(0.064)	
Literacy skills				0.775***
				(0.064)
Municipality characteristics	X	X	X	X
Individual characteristics	X	X	X	X
R squared (adjusted)	0.59	0.66	0.56	0.67
Individuals	121	121	121	121
Municipalities	18	18	18	18

Notes: Ordinary least squares estimation weighted by sampling weights (giving same weight to each municipality). 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 across municipalities, 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. Distance calculations are based on municipalities geographic centroid. Municipality characteristics are unemployment rate in 1999 (i.e., share of unemployed individuals in the working-age population aged 18–65 years), population share of individuals older than 65 in 1999, and average municipality-level wages of workers aged 50–59 years in 2011/2012 (in logs). 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 (2012).

Table 5: Returns to ICT Skills: Cross-Country Estimates

Second stage (Dependent variable: log gross hourly wage)						
	Individual-level ICT skills			Country-level ICT skills		
	(1)	(2)	(3)	(4)	(5)	(6)
ICT skills	0.061**	0.054**	0.079***	0.032**	0.031**	0.080***
	(0.029)	(0.024)	(0.012)	(0.016)	(0.015)	(0.012)
GDP per capita in 1996 (log)	–0.114	–0.211*	–0.243**	–0.021	–0.104	–0.045
	(0.126)	(0.108)	(0.105)	(0.106)	(0.093)	(0.095)
Average wage level 50_59 (log)	0.850***	0.897***	0.875***	0.850***	0.890***	0.800***
	(0.107)	(0.082)	(0.087)	(0.099)	(0.084)	(0.086)
Experience		0.043***	0.042***		0.042***	0.036***
		(0.003)	(0.003)		(0.003)	(0.003)
Experience^2 (/100)		–0.072***	–0.057***		–0.087***	–0.062***
		(0.012)	(0.008)		(0.007)	(0.006)
Female		–0.103***	–0.096***		–0.138***	–0.165***
		(0.018)	(0.016)		(0.018)	(0.019)
Years of schooling			0.020**			0.074***
			(0.009)			(0.004)
First stage (Dependent variable: ICT skills)						
Fixed-line diffusion in 1996	5.979***	6.342***	11.277***	11.266***	11.272***	11.019***
	(1.093)	(0.906)	(1.563)	(1.551)	(1.552)	(1.556)
Kleibergen-Paap F statistic	29.9	49.0	52.0	52.8	52.8	50.1
Individuals	40,670	40,670	40,670	40,670	40,670	40,670
Countries	19	19	19	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. Dependent variable, *log gross hourly wage*, is measured in PPP-USD. In Columns (1)–(3), ICT skills are measured at the individual level and standardized to std. dev. 1 across countries, using the country-level std. dev. as "numeraire" scale. In Columns (4)–(6), ICT skills are the residual of a weighted least-squares regression of individual-level ICT skills on all control variables included in Column (3), aggregated to the country level and standardized to std. dev. 1. *Fixed-line diffusion in 1996:* voice-telephony penetration rate (telephone access lines per inhabitant). *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 in 2011/2012. Fixed-line diffusion, GDP per capita, and average wages of exit-age workers are measured at the country level; all other control 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 (2012).

Table 6: Returns to ICT Skills: Subsample Analysis

Second stage (Dependent variable: log gross hourly wage)	Baseline	Occupation		Sector		Gender		Age	
		Elementary	Managers	Private	Public	Male	Female	"Young"	"Old"
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
ICT skills	0.079***	0.028	0.102***	0.097***	0.033***	0.098***	0.065***	0.090***	0.065***
	(0.012)	(0.031)	(0.017)	(0.013)	(0.009)	(0.018)	(0.016)	(0.017)	(0.012)
Country characteristics	X	X	X	X	X	X	X	X	X
Individual characteristics	X	X	X	X	X	X	X	X	X
First stage (Dependent variable: ICT skills)									
Fixed-line diffusion in 1996	11.277***	11.215***	10.655***	11.654***	11.010***	10.576***	11.937***	11.435***	11.176***
	(1.563)	(2.399)	(2.232)	(1.695)	(1.907)	(1.602)	(1.644)	(1.962)	(1.368)
Kleibergen-Paap F statistic	52.0	21.9	22.8	47.3	33.3	43.6	52.7	34.0	66.8
Individuals	40,670	1,997	3,101	27,203	12,043	19,626	21,044	20,309	20,361
Countries	19	19	19	19	19	19	19	19	19

Notes: Two-stage least squares estimation weighted by sampling weights (giving same weight to each country). Sample is without first-generation immigrants and is restricted to employees aged 20–49 years; in the two last columns, sample is divided into employees aged 20–34 years (Column (8)) and employees aged 35–49 years (Column (9)). Baseline in Column (1) replicates Table 5, Column (3). Sample includes only workers in elementary occupations (ISCO category 9) in Column (2) and workers in managerial occupations (ISCO category 1) in Column (3). 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. Managerial occupations include chief executives, senior officials and legislators, administrative and commercial managers, production and specialised services managers, as well as hospitality, retail and other services managers. 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). 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. 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 (2012).

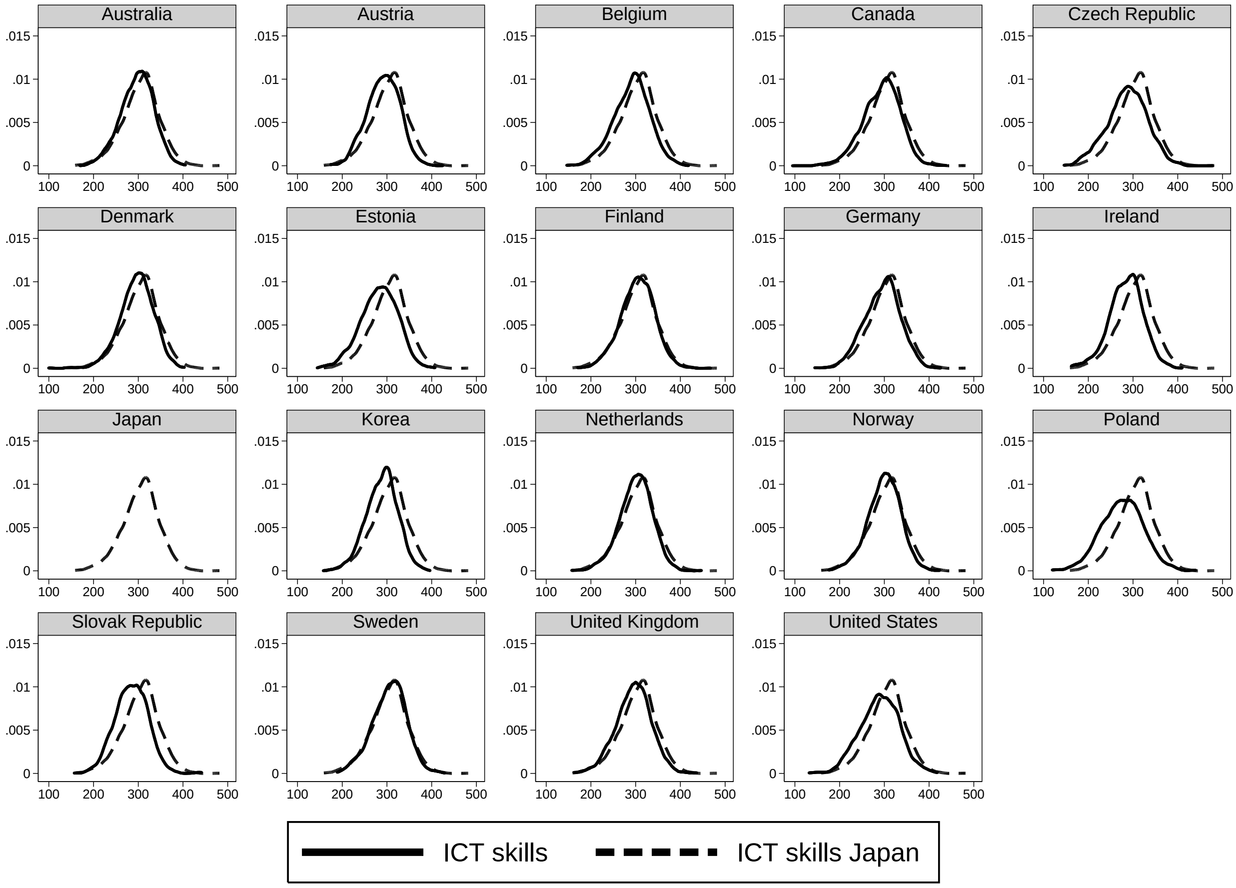
Table 7: Returns to ICT Skills: Within-Country Estimates

Second stage (Dependent variable: log gross hourly wage)						
	Full sample			No own MDF sample		
	(1)	(2)	(3)	(4)	(5)	(6)
ICT skills	0.197***	0.199***	0.152**	0.210**	0.223**	0.174
	(0.070)	(0.064)	(0.076)	(0.095)	(0.095)	(0.111)
Unemployment rate in 1999	–0.084	0.776	0.517	–1.350	–3.897	–2.626
	(0.760)	(0.696)	(0.675)	(5.393)	(6.064)	(5.069)
Population share 65+ in 1999	–0.191	0.122	0.202	1.296	1.602	1.452
	(0.791)	(0.622)	(0.552)	(3.281)	(3.063)	(2.743)
Average wage level 50_59 (log)	0.005	0.035	0.027	0.332*	0.390**	0.321*
	(0.054)	(0.052)	(0.047)	(0.184)	(0.178)	(0.181)
Experience		0.068***	0.058***		0.067***	0.062***
		(0.008)	(0.006)		(0.024)	(0.021)
Experience^2 (/100)		–0.124***	–0.101***		–0.114	–0.100
		(0.031)	(0.022)		(0.087)	(0.075)
Female		–0.158***	–0.161***		–0.168	–0.192*
		(0.032)	(0.028)		(0.116)	(0.107)
Years of schooling			0.061**			0.055
			(0.025)			(0.046)
First stage (Dependent variable: ICT skills)						
Threshold	–0.931***	–0.848***	–0.651***	–1.245***	–1.121***	–0.833**
	(0.246)	(0.240)	(0.190)	(0.330)	(0.336)	(0.329)
Kleibergen-Paap F statistic	14.4	12.5	11.7	14.2	11.1	6.4
Individuals	1,391	1,391	1,391	121	121	121
Municipalities	204	204	204	18	18	18

Notes: Two-stage least squares estimation weighted by sampling weights (giving same weight to each municipality). 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 standardized to std. dev. 1 across municipalities, 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. *Unemployment rate in 1999:* share of unemployed individuals in the working-age population aged 18–65 years, measured in 1999 (i.e., before the emergence of broadband Internet in Germany). *Population share 65+ in 1999:* population share of individuals older than 65 years, measured in 1999. *Average wage level 50_59 (log):* average municipality-level wages of employees aged 50–59 years in 2011/2012. 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. 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 (2012).

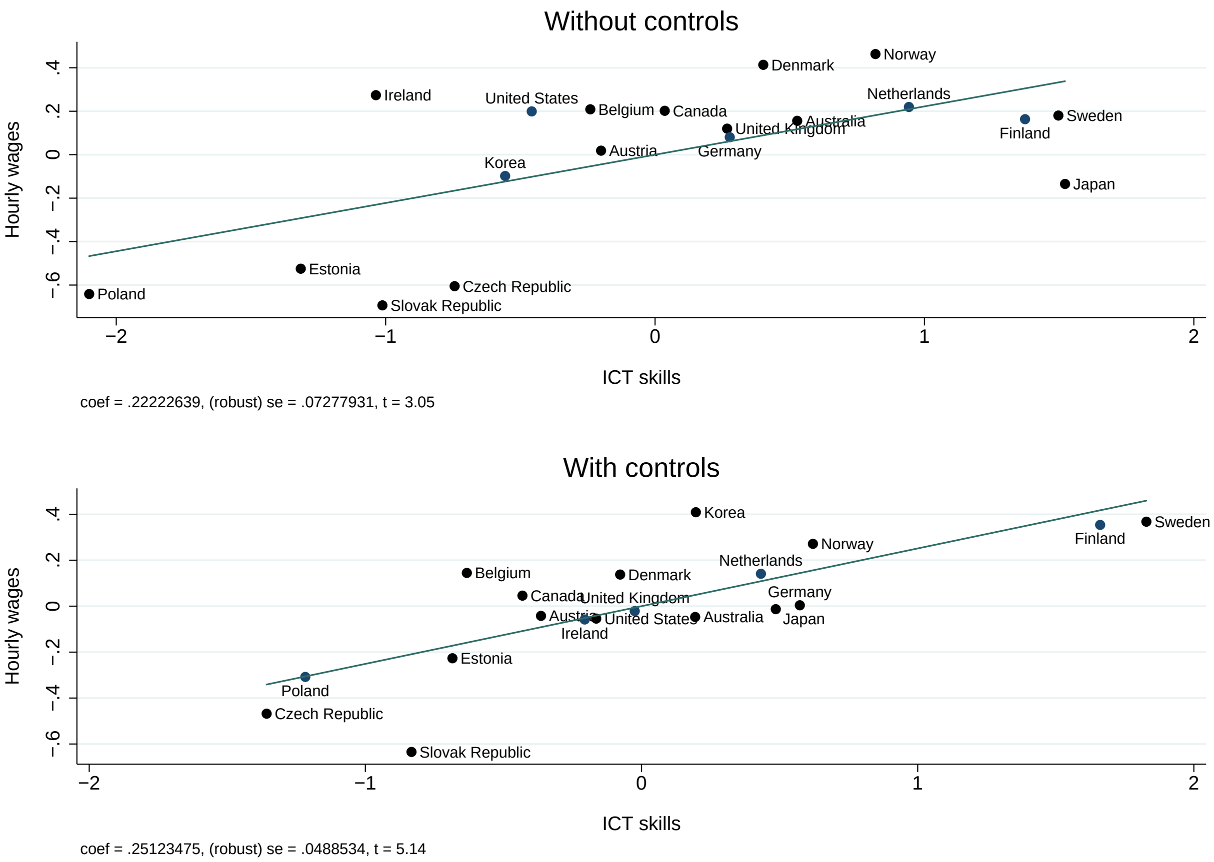
Appendix

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 (2012).

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



Notes: Ordinary least squares estimation. 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:* PIAAC (2012).

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

	Pooled	Australia	Austria	Belgium	Canada	Czech R.	Denmark	Estonia	Finland	Germany
Gross hourly wage	17.3	18.8	16.3	19.2	19.9	9.1	23.6	10.5	18.4	18.5
(in PPP-USD)	(9.8)	(8.3)	(6.3)	(6.5)	(9.0)	(4.2)	(8.1)	(6.3)	(6.8)	(9.4)
ICT skills	293.2	297.4	291.5	291.2	293.4	287.1	296.4	282.4	304.4	295.4
	(40.0)	(36.4)	(36.0)	(40.1)	(41.3)	(43.9)	(37.5)	(41.0)	(37.9)	(39.6)
Numeracy skills	290.6	286.4	292.3	298.4	285.2	287.2	298.0	285.2	304.2	292.8
	(43.8)	(45.3)	(41.3)	(43.0)	(47.3)	(39.1)	(41.4)	(42.5)	(42.6)	(43.9)
Literacy skills	292.6	296.7	284.5	294.0	292.1	284.7	289.8	286.5	309.9	287.6
	(40.1)	(40.2)	(37.5)	(39.6)	(43.1)	(38.5)	(37.6)	(42.0)	(40.4)	(41.9)
Yrs schooling	13.9	14.9	12.7	13.5	13.7	13.7	13.4	12.9	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)	13.8	14.6	15.4	14.8	15.4	13.0	16.8	12.2	12.8	14.3
	(8.4)	(8.4)	(8.6)	(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	40,670	1,909	1,662	1,758	7,474	1,579	1,899	2,127	2,009	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	19.0	21.2
(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	288.6	300.8	299.8	276.0	284.9	305.4	295.3	289.4
	(37.6)	(40.9)	(34.8)	(36.5)	(36.2)	(47.0)	(36.8)	(37.8)	(39.2)	(43.2)
Numeracy skills	277.0	303.1	279.0	298.1	300.1	277.3	292.8	301.2	284.9	273.8
	(44.5)	(39.4)	(36.4)	(41.9)	(44.0)	(43.8)	(37.9)	(42.7)	(46.1)	(50.2)
Literacy skills	285.9	309.7	285.5	303.5	298.0	282.7	286.6	301.3	291.2	288.4
	(40.9)	(33.7)	(34.0)	(38.8)	(37.7)	(42.1)	(33.4)	(38.2)	(42.1)	(43.5)
Yrs schooling	16.2	13.8	14.3	14.0	14.8	14.5	14.2	12.8	13.4	14.3
	(2.3)	(2.3)	(2.3)	(2.1)	(2.2)	(2.6)	(2.5)	(2.2)	(2.3)	(2.5)
Experience (years)	14.0	13.5	9.8	14.6	14.5	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	1,450	1,663	1,929	1,853	1,978	2,358	1,356	1,592	2,804	1,364

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 (2012).

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	0.47	0.50	0.48	0.46	0.61	0.27	0.62	0.31	0.55	0.54
GDP per capita in 1996 (/1000)	24.38	28.37	29.06	27.50	28.90	17.37	29.12	8.47	22.61	27.95
Average wage level 50_59	18.40	20.68	17.57	22.12	21.90	8.57	24.93	8.23	19.01	19.68
Union density	0.30	0.18	0.27	0.55	0.27	0.13	0.67	0.06	0.69	0.18
Employment protection	2.25	1.99	2.44	2.99	1.51	2.66	2.32	2.07	2.17	2.84
Public sector	0.28	0.25	0.26	0.29	0.33	0.26	0.39	0.30	0.36	0.15
Youth unemployment rate	0.17	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	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	23.42	18.76	18.21	22.45	26.10	8.87	8.08	18.80	18.67	24.43
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	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). *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. *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. All country-level variables refer to 2012 unless otherwise noted. See text for details on data sources. Pooled specification gives same weight to each country. *Data sources:* Barro and Lee (2010), ITU, OECD, PIAAC (2012), Statistics Canada, World Bank.

Table A-3: Preexisting Fixed-Line Diffusion and the Extensive vs. Intensive Margin of ICT Skills

Dependent variable indicated in column heading	ICT literacy			ICT skills		
	(1)	(2)	(3)	(4)	(5)	(6)
Fixed-line diffusion in 1996	0.509***	0.519***	0.690***	5.979***	6.342***	11.277***
	(0.123)	(0.129)	(0.166)	(1.093)	(0.906)	(1.563)
GDP per capita in 1996 (log)	0.024	0.041	0.033	0.816	1.199**	1.125*
	(0.070)	(0.071)	(0.069)	(0.513)	(0.475)	(0.538)
Average wage level 50_59 (log)	–0.032	–0.042	–0.104	–1.091***	–1.275***	–2.954***
	(0.066)	(0.067)	(0.072)	(0.352)	(0.386)	(0.640)
Experience		–0.001	–0.003*		–0.018	–0.070**
		(0.001)	(0.001)		(0.026)	(0.025)
Experience^2 (/100)		–0.013***	–0.005		–0.302***	–0.088
		(0.003)	(0.003)		(0.077)	(0.071)
Female		–0.001	–0.011		–0.644***	–0.891***
		(0.007)	(0.006)		(0.124)	(0.101)
Years of schooling			0.026***			0.647***
			(0.005)			(0.025)
R squared (adjusted)	0.05	0.06	0.10	0.03	0.07	0.18
Individuals	46,080	46,080	46,080	40,670	40,670	40,670
Countries	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; in Columns (1)–(3), sample also includes 5,410 respondents with missing ICT test scores. Dependent variable in Columns (1)–(3) is *ICT literacy*, measured as a binary variable that takes the value 1 if an individual has nonmissing ICT test scores and 0 otherwise. ICT skills can be missing in PIAAC due to lacking computer experience reported by the respondent, failing an initial ICT core test, and opting out from the computer-based assessment, respectively (see Section 2 for details). Dependent variable in Columns (4)–(6), *ICT skills*, is 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). *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 in 2011/2012. 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 (2012).

Table A-4: Returns to ICT Skills: Cross-Country Estimates (OLS)

Dependent variable: log gross hourly wage				
	(1)	(2)	(3)	(4)
ICT skills	0.095***	0.119***	0.073***	0.058***
	(0.009)	(0.008)	(0.009)	(0.007)
GDP per capita in 1996 (log)	–0.051	–0.153	–0.089	
	(0.115)	(0.093)	(0.114)	
Average wage level 50_59 (log)	0.850***	0.893***	0.823***	
	(0.101)	(0.080)	(0.099)	
Experience		0.042***	0.037***	0.036***
		(0.003)	(0.003)	(0.003)
Experience^2 (/100)		–0.080***	–0.063***	–0.062***
		(0.007)	(0.006)	(0.005)
Female		–0.123***	–0.150***	–0.162***
		(0.019)	(0.018)	(0.020)
Years of schooling			0.057***	0.067***
			(0.005)	(0.004)
Country fixed effects				X
R squared (adjusted)	0.36	0.45	0.51	0.53
Individuals	40,670	40,670	40,670	40,670
Countries	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. Dependent variable, *log gross hourly wage*, is measured in PPP-USD. ICT skills are standardized to std. dev. 1 across countries. *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 in 2011/2012. 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:* OECD, PIAAC (2012).

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

Third stage (Dependent variable: log gross hourly wage)			
	(1)	(2)	(3)
ICT skills	0.061**	0.054**	0.079***
	(0.030)	(0.025)	(0.013)
Country characteristics	X	X	X
Experience and gender		X	X
Years of schooling			X
Second stage (Dependent variable: ICT skills)			
Broadband diffusion in 2012	22.441*	23.773*	43.615**
	(12.238)	(12.603)	(19.748)
First stage (Dependent variable: broadband diffusion in 2012)			
Fixed-line diffusion in 1996	0.266**	0.267**	0.259*
	(0.136)	(0.136)	(0.133)
Individuals	40,670	40,670	40,670
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). 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. 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 (2012).

Table A-6: Reduced-Form Estimates

Dependent variable: log gross hourly wage	Cross-Country Analysis			Within-Country Analysis					
	Full sample			Full sample			No own MDF sample		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Fixed-line diffusion in 1996	0.363**	0.344*	0.887***						
	(0.171)	(0.169)	(0.176)						
Threshold				–0.193***	–0.178**	–0.109*	–0.281**	–0.270**	–0.170*
				(0.072)	(0.071)	(0.058)	(0.117)	(0.105)	(0.088)
Country/Municipality characteristics	X	X	X	X	X	X	X	X	X
Experience and gender		X	X		X	X		X	X
Years of schooling			X			X			X
R squared (adjusted)	0.33	0.42	0.51	0.01	0.23	0.45	0.08	0.26	0.40
Individuals	40,670	40,670	40,670	1,391	1,391	1,391	121	121	121
Countries/Municipalities	19	19	19	204	204	204	18	18	18

Notes: Ordinary least squares estimation weighted by sampling weights (giving same weight to each country or municipality). Sample: employees aged 20–49 years, no first-generation immigrants. Columns (1)–(3) refer to the international sample consisting of 19 countries; Columns (4)–(6) include all West German municipalities in the sample; Columns (7)–(9) include West German municipalities without an own main distribution frame (MDF). ICT skills are standardized to std. dev. 1, using the country-level std. dev. (Columns (1)–(3)) or the municipality-level std. dev. (Columns (4)–(9)) as "numeraire" scale. *Fixed-line diffusion in 1996:* voice-telephony penetration rate (telephone access lines per inhabitant). *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. Distance calculations are based on municipalities geographic centroid. Country characteristics in Columns (1)–(3) are GDP per capita in 1996 (in logs) and average country-level wages of workers aged 50-59 years in 2011/2012 (in logs). Municipality characteristics in Columns (4)–(9) are unemployment rate in 1999 (i.e., share of unemployed individuals in the working-age population aged 18-65 years), population share of individuals older than 65 in 1999, and average municipality-level wages of workers aged 50-59 years in 2011/2012 (in logs). Robust standard errors, adjusted for clustering at the country or municipality level, in parentheses. Significance levels: * p<0.10, ** p<0.05, *** p<0.01. *Data sources:* German Broadband Atlas, German Federal Statistical Office, ITU, OECD, PIAAC (2012).

Table A-7: Returns to ICT Skills: Interactions with Subsample Indicators

Dependent variable: log gross hourly wage	No country fixed effects				With country fixed effects			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
ICT skills	0.028	0.033***	0.098***	0.065***				
	(0.031)	(0.009)	(0.018)	(0.012)				
× managerial occupation	0.074*				0.083*			
	(0.043)				(0.045)			
× private-sector worker		0.063***				0.063***		
		(0.012)				(0.012)		
× female worker			–0.033				–0.023	
			(0.023)				(0.019)	
× young worker				0.025*				0.026*
				(0.014)				(0.015)
Country characteristics	X	X	X	X				
Country fixed effects					X	X	X	X
Individual characteristics	X	X	X	X	X	X	X	X
Interactions with subsample indicator	X	X	X	X	X	X	X	X
Kleibergen-Paap F main	24.2	24.2	26.8	35.4				
Kleibergen-Paap F interaction	11.4	23.6	26.4	17.0	19.2	51.3	51.8	30.9
Individuals	5,098	39,246	40,670	40,670	5,098	39,246	40,670	40,670
Countries	19	19	19	19	19	19	19	19

Notes: Table shows second stage of two-stage least squares estimation weighted by sampling weights (giving same weight to each country). Sample is without first-generation immigrants and is restricted to employees aged 20–49 years. Dependent variable, *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. In Columns (1) and (5), *managerial occupation* is a binary variable that takes the value 1 if a worker is employed in a managerial occupation (ISCO category 1) and 0 if a worker is employed in an elementary occupation (ISCO category 9). Managerial occupations include chief executives, senior officials and legislators, administrative and commercial managers, production and specialised services managers, as well as hospitality, retail and other services managers. 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. *Private-sector worker*, *female worker*, and *young worker* indicates workers employed in the private sector, female workers, and employees aged 20–34 years, respectively. ICT skills in Columns (1)–(4) are instrumented by fixed-line diffusion in 1996; ICT skills interacted with subsample indicators are instrumented by fixed-line diffusion interacted with the respective subsample indicator. *Kleibergen-Paap F main* refers to instrumentation of ICT skills and *Kleibergen-Paap F interaction* refers to instrumentation of ICT-skills interactions. Country characteristics in Columns (1)–(4) are GDP per capita in 1996 (in logs) and average wages of exit-age workers in 2011/2012 (in logs); in Columns (5)–(8), country-level controls are replaced by country fixed effects. Individual characteristics are quadratic polynomial in work experience, gender, and years of schooling. Regressions also control for a full set of interactions of country characteristics and individual characteristics with the respective subsample indicator. 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 (2012).

Table A-8: Returns to ICT Skills: Age Subsamples

	Baseline (20–49) (1)	Base + exit (20–65) (2)	Prime age (35–54) (3)	Prime + exit (35–65) (4)	All age (16–65) (5)
Second stage (Dependent variable: log gross hourly wage)					
ICT skills	0.079***	0.072***	0.062***	0.058***	0.074***
	(0.012)	(0.012)	(0.011)	(0.011)	(0.014)
Country characteristics	X	X	X	X	X
Individual characteristics	X	X	X	X	X
First stage (Dependent variable: ICT skills)					
Fixed-line diffusion in 1996	11.277***	10.145***	10.265***	9.503***	9.976***
	(1.563)	(1.405)	(1.291)	(1.231)	(1.352)
Kleibergen-Paap F statistic	52.0	52.2	63.3	59.6	54.5
Individuals	40,670	53,879	26,177	33,570	56,626
Countries	19	19	19	19	19

Notes: Two-stage least squares estimation weighted by sampling weights (giving same weight to each country). Sample: employees, no first-generation immigrants. Tables replicates the baseline in Table 5, Column (3) for age ranges indicated in the column header. 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). 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. 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 (2012).

Table A-9: Robustness Checks for Cross-Country IV Model: Further Country-Level Controls

Second stage (Dependent variable: log gross hourly wage)								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
ICT skills	0.079***	0.064***	0.081***	0.082***	0.073***	0.083***	0.071***	0.069***
	(0.012)	(0.015)	(0.011)	(0.012)	(0.014)	(0.013)	(0.014)	(0.022)
Union density		0.198**						–0.028
		(0.079)						(0.161)
Employment protection			0.017					0.016
			(0.021)					(0.032)
Youth unemployment rate				0.293				0.530
				(0.241)				(0.415)
Service share					–0.329			–0.537*
					(0.230)			(0.326)
Share tertiary educated						–0.441		0.079
						(0.358)		(0.463)
Mobile diffusion							0.133**	0.172**
							(0.064)	(0.083)
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	11.277***	10.038***	12.372***	11.043***	11.520***	11.777***	10.193***	9.987***
	(1.563)	(1.740)	(1.453)	(1.500)	(1.655)	(1.627)	(1.463)	(1.196)
Kleibergen-Paap F statistic	52.0	33.3	72.5	54.2	48.5	52.4	48.5	69.8
Individuals	40,670	40,670	40,670	40,670	40,670	40,670	40,670	40,670
Countries	19	19	19	19	19	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. 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). Baseline in Column (1) replicates Table 5, Column (3). *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. *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. All country-level control variables refer to 2012 unless otherwise noted. 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. 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 (2012), Statistics Canada, World Bank.

Table A-10: Robustness Checks for Cross-Country IV Model: Further Individual-Level Controls

Second stage (Dependent variable: log gross hourly wage)					
	(1)	(2)	(3)	(4)	(5)
ICT skills	0.079***	0.080***	0.082***	0.078***	0.083***
	(0.012)	(0.013)	(0.014)	(0.011)	(0.013)
Full-time		–0.028			–0.034
		(0.052)			(0.056)
Parental education			–0.029***		–0.030***
			(0.011)		(0.010)
Health				0.026***	0.027***
				(0.008)	(0.008)
Country characteristics	X	X	X	X	X
Individual characteristics	X	X	X	X	X
First stage (Dependent variable: ICT skills)					
Fixed-line diffusion in 1996	11.277***	11.262***	10.110***	11.643***	10.516***
	(1.563)	(1.571)	(1.557)	(1.625)	(1.556)
Kleibergen-Paap F statistic	52.0	51.4	42.2	51.3	45.7
Individuals	40,670	40,670	39,043	33,192	31,974
Countries	19	19	19	18	18

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. Columns (4) and (5) are 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). Baseline in Column (1) replicates Table 5, Column (3). *Full-time:* 1 = working more than 30 hours per week (Australia and Austria: self-reported information whether a respondent works full-time; Canada: no information on full-time working status). *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. 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. 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 (2012).

Table A-11: 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	0.207***	0.209***	0.167*	0.226**	0.256**	0.225
	(0.075)	(0.069)	(0.086)	(0.107)	(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	18.203**	16.452**	12.921**	26.148**	24.777*	19.313
	(7.483)	(6.503)	(5.857)	(13.125)	(12.900)	(11.843)
First stage (Dependent variable: broadband availability)						
Threshold	–0.051***	–0.052***	–0.050***	–0.048**	–0.045**	–0.042*
	(0.019)	(0.019)	(0.018)	(0.023)	(0.022)	(0.022)
Individuals	1,391	1,391	1,391	121	121	121
Municipalities	204	204	204	18	18	18

Notes: Three-equation seemingly unrelated regression estimation weighted by sampling weights (giving same weight to each municipality). 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 standardized to std. dev. 1 across municipalities, 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. Distance calculations are based on municipalities geographic centroid. Municipality characteristics are unemployment rate in 1999 (i.e., share of unemployed individuals in the working-age population aged 18–65), population share of individuals older than 65 in 1999, and average municipality-level wages of workers aged 50–59 years in 2011/2012 (in logs). Models in Columns (5) and (6) are with unadjusted sampling weights because the estimator did not converge with adjusted weights. 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 (2012).

Table A-12: Robustness Checks for Within-Country IV Model: Further Individual-Level Controls

Second stage (Dependent variable: log gross hourly wage)					
	(1)	(2)	(3)	(4)	(5)
ICT skills	0.152**	0.151**	0.201**	0.153**	0.204**
	(0.076)	(0.076)	(0.092)	(0.077)	(0.094)
Full-time		0.113***			0.100**
		(0.041)			(0.045)
Parental education			–0.087**		–0.088*
			(0.044)		(0.045)
Health				0.039**	0.043**
				(0.018)	(0.021)
Municipality characteristics	X	X	X	X	X
Individual characteristics	X	X	X	X	X
First stage (Dependent variable: ICT skills)					
Threshold	–0.651***	–0.652***	–0.596***	–0.651***	–0.595***
	(0.190)	(0.190)	(0.207)	(0.190)	(0.208)
Kleibergen-Paap F statistic	11.7	11.8	8.3	11.7	8.2
Individuals	1,391	1,391	1,336	1,391	1,336
Municipalities	204	204	203	204	203

Notes: Two-stage least squares estimation weighted by sampling weights (giving same weight to each municipality). Sample: West German employees aged 20–49 years, no first-generation immigrants. ICT skills are standardized to std. dev. 1 across municipalities, 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. Distance calculations are based on municipalities geographic centroid. *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. *Firm size:* 1 = 1–10 employees; 2 = 11–50 employees; 3 = 51–250 employees; 4 = 251–1,000 employees; 5 = more than 1,000 employees. Municipality characteristics are unemployment rate in 1999 (i.e., share of unemployed individuals in the working-age population aged 18–65 years), population share of individuals older than 65 in 1999, and average municipality-level wage of workers aged 50–59 years in 2011/2012 (in logs). 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 (2012).