

Returns to ICT Skills*

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Abstract

How important is mastering information and communication technology (ICT) in modern labor markets? We answer this question with unique data on ICT skills tested in 19 countries. Our two instrumental-variable models exploit technologically induced variation in broadband Internet availability that gives rise to variation in ICT skills across countries and German municipalities. We find that a one-standard-deviation increase in ICT skills raises earnings by about 25 percent. Exogenous broadband availability cannot explain numeracy or literacy skills, suggesting that estimated returns are unaffected by general ability. One mechanism driving positive returns is selection into occupations with high abstract task content.

Keywords: ICT skills; broadband; earnings; international comparisons

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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 this terminology by arguing that “the online world is becoming a bigger part of everything we do. No wonder these [ICT] skills are becoming central in the job market.”¹ The statement is intuitively plausible, but, as of yet, there is no convincing empirical evidence on how the labor market rewards ICT skills. The main reasons for this lack are the unavailability of data that measure ICT skills consistently within or across countries, and the difficulty of drawing credible inferences when it is unknown whether an individual’s level of ICT skills is simply a reflection of general ability. Using novel, internationally comparable data from the Programme for the International Assessment of Adult Competencies (PIAAC) on individuals’ skills in ICT and other domains across 19 countries, this paper provides the first systematic assessment of the wage returns to ICT skills.

Our identification strategy is based on the idea that ICT skills are developed by performing ICT-related tasks, which is facilitated by Internet access.² We implement two instrumental-variable (IV) strategies that exploit technologically induced variation in Internet availability across countries and across small geographical areas within a single country. In the cross-country strategy, this variation stems from international differences in the rollout of preexisting fixed-line voice-telephony networks that determine the timing of introduction and diffusion of high-speed Internet via broadband. These networks affect only the supply side of broadband diffusion in a country and therefore rule out demand-side effects based on differences in wealth and broadband-deployment policies (Czernich, Falck, Kretschmer, and Woessmann, 2011). To address the concern that richer and more productive countries have more extensive fixed-line networks as well as higher wages and more skilled workers, we exploit the pronounced age pattern in the impact of exogenous broadband availability on ICT skills. The youngest cohorts in PIAAC were toddlers when broadband emerged; the oldest cohorts were already reluctant to use the new technology. This allows us to combine the IV estimation with a difference-in-differences strategy, effectively identifying returns to ICT skills based on differences in ICT skills and wages between age cohorts within countries.

¹ <http://www.getonlineweek.eu/vice-president-neelie-kroes-says-digital-literacy-and-e-skills-are-the-new-literacy/>; accessed October 14, 2016.

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

In the second IV strategy, we exploit technological peculiarities that led to variation in broadband availability at a very fine regional level within Germany. Specifically, in the western part of Germany, the voice-telephony network was designed in the 1960s with the goal of providing universal telephone service to German households. In traditional telephone networks, the distance between a household and the main network node (“last mile”) was irrelevant for the quality of voice-telephony services; however, about 40 years later, the last-mile distance restricted the availability of broadband Internet. Beyond a certain distance threshold, high-speed Internet access was not feasible without major infrastructure investment, a situation that excluded a considerable share of West German municipalities from early broadband Internet access (Falck, Gold, and Heblich, 2014).³ We also control for the economic situation in a municipality before the emergence of broadband, which may be correlated with both baseline fixed-line networks and today’s wages.

We find that the extent and technical peculiarities of the preexisting fixed-line infrastructure are significantly related to individuals’ ICT skills, supporting the assertion that a higher (technologically determined) probability of having Internet access leads to learning-by-doing in ICT skills. Drawing only on variation in ICT skills attributable to exogenously determined broadband access, both IV strategies indicate a positive effect of ICT skills on wages that is economically and statistically significant. In the cross-country analysis, an increase in ICT skills by one standard deviation (SD) leads to a 24 percent increase in employee wages. In terms of magnitude, the estimate implies that if an average worker in the United States increased her ICT skills to the level of an average worker in Japan (i.e., the best-performing country in the skill assessment), her wages would increase by about 8 percent; this is close to the well-identified estimates on the returns to one additional year of schooling in developed countries. In Germany, estimated returns to ICT skills are even larger at 31 percent.

A series of validity checks bolster confidence in our IV strategies. First, we show that our instruments do not predict the ICT skills of first-generation immigrants, who are unlikely to have acquired ICT skills in the PIAAC test country. Nor are the instruments associated with any appreciable changes in numeracy or literacy skills, which we consider strong evidence that our identification strategies isolate the effect of ICT skills (vis-à-vis generic skills or general ability) on

³ Other studies have used variation in technological broadband availability across locations as a source of exogenous variation in actual use (e.g., Bertsek, 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 decisions made by profit-maximizing telecommunication carriers.

wages.⁴ Second, we provide a careful assessment of the exclusion restriction of our IV approach that exogenous broadband availability affects today’s wages only through individuals’ ICT skills, and not directly in any other way. In fact, we account for the two most prominent channels of direct productivity effects of broadband: the introduction of online job search channels, which increases the quality of job matching, and that broadband is directly productive for firms, affecting wages of workers irrespective of their own usage of ICT skills. For instance, we control for alternative broadband access technologies which potentially increased firm productivity but did not induce learning-by-doing effects in ICT skills. Third, we show that households in Germany without broadband Internet access do not selectively relocate to regions where broadband is available.

A unique feature of the PIAAC survey is that it combines individual-level information on ICT skills, wages, and detailed occupation in a single dataset. This allows us to shed light on a potential mechanism behind the positive returns to ICT skills, namely, that the proliferation of personal computers caused a shift away from routine tasks—that is, those more amenable to automatization—toward problem-solving and complex communication tasks (typically called “nonroutine abstract tasks”). This argument was first made by Autor, Levy, and Murnane (2003) when developing their task-based approach to skill-biased technological change.⁵ We expect that the complementarity of computers (requiring ICT skills) and abstract tasks allows workers with high ICT skills to select into abstract jobs and to benefit from the wage premia these jobs pay. To test whether occupational selection is an avenue through which ICT skills lead to higher wages, we estimate our IV models with abstract, routine, and manual task content as outcomes. We find that higher ICT skills increase the abstract task content of jobs and decrease their routine and manual task content. Back-of-the-envelope calculations suggest that occupational selection explains about two-thirds of the wage increase caused by higher ICT skills.⁶

⁴ Our result that exogenous Internet availability affects only a specific set of skills is in line with Malamud and Pop-Eleches (2011). Exploiting an income threshold for eligibility for a computer voucher in Romania, they show that home computer ownership has zero or even negative effects on student achievement in math and reading but supports the development of ICT-related skills. Likewise, Faber, Sanchis-Guarner, and Weinhardt (2015) use a boundary-discontinuities strategy in the United Kingdom that relies on a similar idea as our within-Germany model, and find that the availability of fast Internet at students’ homes has no effect on their test scores.

⁵ See also Autor, Katz, and Kearney (2006, 2008), Goos and Manning (2007), Black and Spitz-Oener (2010), 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). Acemoglu and Autor (2011) as well as Autor (2015) provide recent reviews of this literature.

⁶ These results are in line with Gaggl and Wright (2015), who provide evidence for the United Kingdom that ICT investments increase the earnings and employment of workers engaged in abstract tasks. See also Akerman, Gaarder, and Mogstad (2015) for a task-based explanation of labor-market effects of broadband Internet adoption in Norway.

Our paper is directly related to the literature on the wage returns to computer skills.⁷ This literature typically relies on self-reported measures of computer *use*, for instance, from the U.S. Current Population Survey (e.g., Krueger, 1993) or the British National Child Development Study (Dolton and Makepeace, 2004), implicitly assuming that workers with stronger skills are allocated to jobs in which computer skills are required. A few papers use self-reported measures of computer *knowledge* or *skills*, provided, for instance, in the German Qualification and Career Survey (e.g., DiNardo and Pischke, 1997) or in the British Skills Survey (e.g., Borghans and ter Weel, 2004).⁸ Still, these measures are imperfect proxies for a worker’s true skills because they are very crude, typically limiting answers to only a few categories,⁹ suffer from reporting bias, and assume that workers are aware of the full skill distribution in the population. Moreover, existing worker surveys are not harmonized across countries, making an international analysis impossible. Furthermore, the returns from one or two decades ago may no longer be good indicators of the situation in economies that have undergone substantial technological change (discussed in, e.g., Autor, Levy, and Murnane, 2003; Goldin and Katz, 2008; Acemoglu and Autor, 2011). By using recent assessment data on workers’ ICT skills that are internationally comparable, we provide novel insights into the value of mastering information and communication technologies in the modern labor market.

Previous literature highlights the empirical challenges of attempting to estimate the causal effects of computer skills. For example, an influential paper by DiNardo and Pischke (1997) suggests that computer users have unobserved skills that might have little to do with computers per se but that increase their productivity. The authors demonstrate this by showing that positive wage effects can also be found for pencil use at work, which are similar in magnitude to those of computer use. Based on this striking finding, they conclude that returns to computer use at work must be biased by unobserved skills of the users. To our knowledge, our paper is the first to use a direct measure of ICT skills and estimate their impact on wages. Since we also have information on worker skills in other domains, we can 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.

⁷ See Draca, Sadun, and Van Reenen (2007) for a recent review.

⁸ A very recent example for the usage of self-reported computer skills is the study by Fairlie and Bahr (2016). They follow community-college students from disadvantaged backgrounds who were randomly assigned computers in 2006 for seven years. Their results indicate no effect of computer skills on earnings for these early-career workers.

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

Our paper also contributes 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 for assessing the magnitude of the labor-market returns to cognitive skills, as most of the previous evidence stems from the small number of U.S. panel datasets that follow tested students into their initial jobs.¹⁰ An exception is the work by Hanushek, Schwerdt, Wiederhold, and Woessmann (2015), who use the PIAAC data to produce new international evidence on the wage returns to cognitive skills. However, the authors do not specifically investigate the returns to ICT skills, which is the aim of this study. They explore issues of causality by using several IV approaches, but exploit plausibly exogenous variation in skills only in the United States, using changes in compulsory schooling laws across states over time, an approach that 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 has relevance 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.¹¹ The literature on how e-learning affects student achievement mostly shows no or very weak effects, albeit positive effects are found for a few types of uses (Falck, Mang, and Woessmann, 2015). Our results suggest that developing ICT skills through e-learning (as shown, e.g., in Malamud and Pop-Eleches, 2011) might prove beneficial for students' future labor-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 two IV strategies. Section 4 presents the returns-to-ICT-skills estimates. Section 5 provides an analysis of the validity of our instruments, followed by various robustness checks in Section 6. Section 7 investigates whether occupational selection explains positive returns to ICT skills. Section 8 concludes and derives some implications for policy-making.

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 A very recent example of e-learning is the German "Educational offensive for the digital knowledge-based society" by the Federal Ministry of Education and Research, which aims to spend 5 billion euro to equip schools with IT infrastructure.

2. ICT Skills

One of the core features of this paper is its use of new and consistent international data on the ICT skills of the adult population. These data come from the Programme for the International Assessment of Adult Competencies (PIAAC). PIAAC is the product of collaboration between participating countries through the Organization for Economic Co-operation and Development (OECD), and made use of leading international expertise to develop valid comparisons of skills across countries and cultures. The survey was conducted between August 2011 and March 2012 in 24 countries, which together represent about 75 percent of worldwide GDP.¹² PIAAC was designed to provide representative measures of the 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.¹³

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.¹⁴ The individual-level correlation of ICT skills with literacy (numeracy) is 0.78 (0.73), which is less strong than the correlation between numeracy and literacy

¹² The countries that participated in PIAAC are Australia, Austria, Belgium (Flanders), Canada, Cyprus, the Czech Republic, Denmark, Estonia, Finland, France, Germany, Ireland, Italy, Japan, Korea, the Netherlands, Norway, Poland, the Russian Federation, the Slovak Republic, Spain, Sweden, the United Kingdom (England and Northern Ireland), and the United States. Canada (November 2011 to June 2012) and France (September to November 2012) were the only countries with a different survey period.

¹³ The PIAAC Public Use File reports hourly wages for Austria, Canada, Germany, Sweden, and the United States only as a worker's decile rank in the country-specific wage distribution. For Germany, we obtained the Scientific Use File, which contains continuous wage information. For the remaining countries, we follow Hanushek, Schwerdt, Wiederhold, and Woessmann (2015) in assigning the decile median of hourly wages to each survey participant belonging to the respective decile of the country-specific wage distribution. Moreover, in each country, we trim the bottom and top 1 percent of the wage distribution to limit the influence of outliers. ¹⁴ 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 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.

(0.82). Nevertheless, all three skill domains appear to measure distinct dimensions of a respondent's skill set.¹⁵

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, 2013a, p. 86).¹⁶ 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 a combination of several applications, for example, managing requests to reserve a meeting room using a web-based reservation system and sending out e-mails to decline reservation requests that could not be accommodated.¹⁷ In general, ICT skills as assessed in PIAAC measure the extent to which a participant is capable of using modern information and communication tools to get along in a digital world. PIAAC's ICT test does not reflect proficiency in more specific computer skills like advanced programming.

ICT skills were assessed in a computer-based mode, so some basic knowledge regarding the use of computers was required to even participate in the ICT skill test; 7.5 percent of all PIAAC participants indicated in the background questionnaire that they had no prior computer experience and thus these participants did not take part in the computer-based assessment. Instead, they took the survey via pencil and paper, and only their numeracy and literacy skills were tested. Participants who reported at least basic knowledge of computer-based applications were issued an ICT core test, which assessed basic ICT competencies such as using a keyboard/mouse or scrolling through text on the screen; 5.1 percent of all participants did not pass this test and were excluded from the ICT skills assessment. Moreover, 9.8 percent of all participants opted to take the paper-based assessment

¹⁵ The International Adult Literacy Survey (IALS), the predecessor of PIAAC, suffered from pair-wise correlations of individual skill domains that exceeded 0.9, making it virtually impossible to distinguish between different skills. Moreover, ICT skills were not assessed in IALS.

¹⁶ Literacy is the ability to understand, evaluate, use, and engage with written texts so as to participate in society, achieve one's goals, and develop one's knowledge and potential. Numeracy is the ability to access, use, interpret, and communicate mathematical information and ideas in order to engage in and manage the mathematical demands of a range of situations in adult life. See OECD (2013a) for details.

¹⁷ See OECD (2013a, p. 89, 2015, p. 39f.) for other examples of problem scenarios used in PIAAC to test participants' ICT skills. The ICT tasks to be solved were of three levels of difficulty.

without first taking the ICT core assessment, even though they reported some prior experience with computers.¹⁸ Persons without an ICT skills score are excluded from our main estimation sample.¹⁹

Assessing ICT skills was an international option. Cyprus, France, Italy, and Spain did not take part in the ICT skills assessment, which leaves us with data for 19 countries.²⁰ We also drop individuals aged 16–19 years because most have not finished their education. Moreover, our identification strategy (see Section 3) requires that we can ascribe respondents' ICT skills to broadband Internet access in the PIAAC test country. We therefore exclude first-generation immigrants, who often have developed their ICT skills in a country other than the PIAAC test country.²¹ The resulting sample includes 53,879 individual-level observations.²²

Figure 1 depicts ICT skills by country, showing mean, median, and interquartile range of the ICT skills distribution. The average (median) level of ICT skill across PIAAC countries is 287 points (289 points), with a SD of 41 points.²³ Respondents in Japan, Sweden, Australia, and the Netherlands have the highest average scores; respondents in the former communist countries (the Czech Republic, Estonia, Poland, and the Slovak Republic) and Ireland score lowest. The difference between Japan (the best-performing country with 299 points) and Poland (the worst-performing country with 273 points) amounts to roughly 0.6 SD.²⁴ Countries also differ in how ICT skills are distributed in the population. The ICT skill distribution is widest in Poland, the United States, and the Czech Republic,

¹⁸ Not surprisingly, people who took the paper-based assessment are, on average, older than people who took the computer-based assessment, regardless of the reason for this choice (i.e., no computer experience, failed in core ICT test, opting out). People whose skills were assessed via the paper-based format also tend to use the Internet and computers very infrequently, if at all, at home. Moreover, they have, on average, lower numeracy and literacy skills. See also Rammstedt (2013) and OECD (2015).

¹⁹ In Section 6 below, we discuss results from an extended sample that includes persons with missing ICT skills.

²⁰ We also exclude the Russian Federation from the analysis. According to OECD (2013a), 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 Placebo tests and robustness analyses (see Sections 5 and 6) show the appropriateness of these sample restrictions.

²² The international PIAAC sample with 24 countries contains 164,997 observations. Without the four countries that opted out of the ICT skills assessment and the Russian Federation, sample size is 138,383 observations. ICT skills could not be measured for 32,831 individuals. We restrict the sample to persons who are employed at the time of the PIAAC survey, trim the bottom and top 1 percent of the wage distribution, and exclude self-employed who do not report hourly wage information in PIAAC, leading to a decrease in sample size by 41,549 observations. The age restriction further reduces the sample by 2,989 workers and dropping first-generation immigrants reduces it by 6,349 workers. Finally, we exclude 786 workers with missing information on migration status, gender, education, full-time status, or work experience, resulting in a sample of 53,879 workers.

²³ Both mean and SD of numeracy and literacy skills are very similar in the international sample (see Table A-1).

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 lack of computer experience (self-reported or failure in ICT core test) 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 -0.38 .

where the 25th–75th percentile skill range amounts to more than 60 points, and is most compressed in Korea, with an interquartile range of less than 50 points.

<< Figure 1 about here >>

Figure 2 shows that ICT skills tend to decrease by age (298 points for age group 20–34 vs. 267 points for age group 55–65). Similarly, tertiary-educated workers outperform workers with below-tertiary education, but not by a large margin (301 points vs. 277 points). However, there is substantial variation in ICT skills for all age ranges and education levels.

<< Figure 2 about here >>

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

In the econometric analysis, we standardize ICT skills to have mean zero and SD one²⁵ and always employ the sample weights provided in PIAAC.²⁶

²⁵ In the international analysis, we standardize scores using the cross-country SD; in the German analysis, we use the within-Germany SD. Both are almost exactly at 41 PIAAC points.

²⁶ In the cross-country analysis, we restrict the sum of all individual-level weights within a country to equal one to account for differences in sample size across countries; we employ an analogous weight adjustment that restricts the sum of all individual-level weights within a municipality to equal one in the within-Germany analysis.

3. Identification Strategy

3.1 Empirical Model

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

$$\log w_{ic} = \beta_0 + \beta_1 ICT_{ic} + \mathbf{X}_{ic}\boldsymbol{\beta}_2 + \mu_c + \varepsilon_{ic}. \quad (1)$$

w_{ic} is gross hourly wages earned by individual i living in country c and ICT_{ic} are the individual’s ICT skills. $\mathbf{X}_{ic}$ is a vector of individual-level variables including age and gender. Following Hanushek, Schwerdt, Wiederhold, and Woessmann (2015), we estimate an earnings function without years of schooling, which is one of several inputs into cognitive skills.²⁷ μ_c are country fixed effects that account for any differences in the countries’ wage levels. ε_{ic} is a standard error term. The coefficient of interest is β_1 , which shows the wage change in percent when ICT skills increase by one SD.²⁸

In this basic regression framework, β_1 can hardly be interpreted as the causal effect of ICT skills on wages. The most obvious reasons for β_1 being a biased estimate of the true returns to ICT skills are measurement error, reverse causality, and omitted variables (for a discussion, see Hanushek, Schwerdt, Wiederhold, and Woessmann, 2015). Measurement error may occur if cognitive skills in PIAAC are just an error-ridden measure of the human capital relevant in the labor market. 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.²⁹ Moreover, higher earnings

²⁷ In Section 5.1, we analyze returns to ICT skills for different educational groups.

²⁸ For 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).

²⁹ 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. See also Appendix B.

may actually lead to improvements in ICT skills, giving rise to the problem of reverse causality. Better jobs may more likely require and reinforce skills or they may provide the resources to invest in adult education, training, or computer courses. Reverse causality will likely lead to an upward bias of the returns-to-ICT-skills estimates. Finally, omitted-variable bias may arise because unobserved variables like non-cognitive skills, personality traits, or family background could directly influence earnings and may also be related to ICT skills. The direction of the omitted-variable bias is not clear a priori. For instance, Malamud and Pop-Eleches (2011) find that home computers increase computer knowledge but worsen grades, implying that ICT skills may be negatively related to other skills. This would bias the least squares estimates downward. A positive correlation of ICT skills with other unobserved variables that are valued in the labor market would bias the least squares estimates upward.

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

3.2 *Characteristics of the DSL Network*

DSL, one of the two dominant fixed-line broadband Internet access technologies worldwide,³⁰ relies on the copper wires of the voice-telephony network connecting households with the main distribution frame (MDF).³¹ The voice-telephony networks were typically planned and rolled out by state monopolies, so decisions concerning infrastructure deployment were usually made on the basis of political rather than commercial considerations. Although these copper wires were used for fixed-line voice calls before the emergence of DSL technology, they could be upgraded to provide DSL by installing new hardware (so called DSLAMs) at the MDFs, making data traffic at high bandwidths to the telecommunication carrier's backbone network feasible (see Figure 3). This technological feature of DSL technology made broadband rollout substantially cheaper compared to having to roll out new

³⁰ The major alternative fixed-line access technology is broadband access via cable TV networks (see Section 5.2).

³¹ In the United Kingdom, the MDF is usually referred to as the "Local Exchange"; in the United States, it is called the "Central Office."

wires to households. Even in countries where fiber was rolled out to the curbs or homes, the existing ducts of traditional fixed-line networks were used to reduce the deployment cost of broadband. Thus, the existing fixed-line infrastructure initially built for purposes other than the provision of broadband allowed for an economically viable widespread diffusion of broadband Internet (Czernich, Falck, Kretschmer, and Woessmann, 2011). In consequence, countries with a high fixed-line penetration before the introduction of DSL could roll out broadband earlier and reached a larger share of the population faster than countries lagging behind in fixed-line infrastructure (see Section 3.3).

At the same time, the reliance of broadband rollout on traditional voice-telephony networks led to an uneven distribution of broadband Internet access within countries in the early years of the Internet era. While the distance between the household and the MDF, the so-called last mile (see Figure 3), is irrelevant for the quality of voice-telephony services, it determines the feasibility of DSL technology and therefore plays a crucial role in broadband access. Above a certain last-mile distance, DSL is no longer feasible without major infrastructure investment. This technological peculiarity of DSL technology induces exogenous variation in broadband access at a very fine regional level (see Section 3.4).

<< Figure 3 about here >>

3.3 *Cross-Country Instrumental-Variable Model*

We begin by showing that preexisting fixed-line infrastructure affected the introduction and initial diffusion of broadband Internet. Figure 4 reveals a negative relationship between a country's fixed-line infrastructure in 1996 (broadband first emerged in Canada in 1997) and the year broadband was introduced in the country.³² Similarly, Figure 5 shows a strong positive relationship between preexisting fixed-line diffusion and broadband diffusion in 2006, that is, several years after the first

³² In the figure, the year of broadband Internet introduction is defined as the year in which broadband infrastructure reached 5 percent of a country's population.

introduction of broadband.³³ Both figures indicate that broadband infrastructure relies on traditional fixed-line networks.

However, the reliance of broadband Internet diffusion on preexisting fixed-line networks became substantially weaker over time. In fact, broadband diffusion in 2012 (i.e., the year of the PIAAC survey) is not significantly related to initial fixed-line diffusion (orange line in Figure 5). One reason cross-country differences in broadband penetration tend to flatten out over time is the S-shaped diffusion pattern of new technologies (Griliches, 1957; Geroski, 2000): countries that adopted broadband Internet earlier reach the concave part of the diffusion curve earlier, and thus broadband penetration grows more slowly than in countries that introduced broadband later. Moreover, new technologies such as mobile broadband infrastructure attenuate the importance of DSL for accessing the Internet.³⁴

<<Figures 4 and 5 about here >>

The variation in broadband Internet availability that we draw on to explain ICT skills thus mainly comes from the early years of the Internet era. One question that naturally arises is to what extent broadband Internet in these early years provided added value to consumers compared to technologies already available. Before the introduction of broadband Internet, only low-speed Internet access via dial-up-type technologies such as modems and ISDN was feasible. Even in the best case of high-end ISDN access, the maximum available speed was 128 kbit/s. The bandwidth increased substantially with the emergence of broadband, reducing limitations to Internet use as well as the excessive waiting times for loading web pages. According to a study by the Pew Internet and American Life Project (2002), even simple activities such as writing an e-mail are carried out more often when broadband access instead of dial-up technology is available in a household (52 vs. 67 percent). The advantage of

³³ Both figures are added-variable plots that account for pre-broadband values of GDP per capita, population size, average years of schooling, and cable TV diffusion.

³⁴ For instance, according to the annual ICT survey conducted by the German Federal Statistical Office, the share of German firms that use mobile broadband technologies to access the Internet more than doubled between 2008 and 2012, from 14 percent to 33 percent. In contrast, the share of firms using DSL to connect to the Internet has held constant at 80 percent since 2008 (Federal Statistical Office, 2012). However, given that most firms rely on DSL to access the Internet and are therefore also affected if DSL is unavailable for technical reasons, our IV strategy is likely picking up learning-by-doing effects in the accumulation of ICT skills at work *and* at home.

fast Internet access is even more pronounced for information-seeking activities (13 vs. 30 percent), also including job-related research (14 vs. 36 percent). We therefore expect that primarily the availability of broadband Internet (vis-à-vis Internet access via dial-up technology) induces learning-by-doing effects in the accumulation of ICT skills. Note, however, that Internet use beyond the mere consumption of content (e.g., podcasting, blogging, social networking), as prevalent the second half of the 2000s, is less likely to contribute to the learning-by-doing effects we identify.

The fact that our identifying variation stems from the early phase of broadband diffusion induces a distinct age pattern in the impact of technologically determined broadband availability on the ICT skills of PIAAC respondents, which we exploit in the cross-country analysis. Figure 6 reveals an inverted U-shaped age pattern in the effect of technologically determined broadband availability on ICT skills.³⁵ The young cohorts in the PIAAC sample (16–34 years) were toddlers or still at school when broadband Internet emerged (i.e., in 1997), and thus were not using this technology professionally.³⁶ We observe the strongest impact of technologically induced broadband availability for PIAAC respondents aged 35–44 years, who entered the labor market or started university in the early years of the Internet era. This is consistent with the notion that the most prominent applications of the Internet in these years were writing e-mails and looking up information. The effect of early broadband availability diminishes for older ages, which is explained by the psychological literature stressing that older individuals suffer more often from computer anxiety and have less computer self-efficacy (Czaja et al., 2006).³⁷ Note that Figure 6 is very similar when adjusting ICT skills by the age-specific SD to avoid potential ceiling effects (results available upon request).

<<Figure 6 about here >>

³⁵ We also observe an inverted U-shaped age pattern in computer use when looking at data from the time use survey conducted by the German Federal Statistical Office. In 2001/2002, 13 percent of computer users were 10–17 years old, 21.4 percent were 18–29 years old, 15 percent were 30–44 years old, and only 4.4 percent were 45–64 years old.

³⁶ Many of the more leisure-oriented Internet applications (e.g., Facebook, YouTube, and Twitter) emerged only in the second half of the 2000s.

³⁷ In Figure A-1, we observe that in countries with higher exogenous broadband availability, older individuals less often report not having any experience with computers and are also less likely to opt out of the ICT assessment. This evidence suggests that being exposed to the Internet increases individuals' confidence in their computer and Internet abilities over time. We find no distinct age pattern in the effect of exogenous broadband availability on failing the ICT core test, indicating that by 2012, all countries were equally able to equip their inhabitants with very basic ICT skills.

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

$$ICT_{ic} = \alpha_0 + \sum_a \alpha_{1a} a_{ic} \times FD_c + \mathbf{X}_{ic} \boldsymbol{\alpha}_2 + \mu_c + \vartheta_{ic}. \quad (2)$$

Here, our instruments are interactions of the country-level fixed-line diffusion in 1996, FD_c (which determines broadband availability in the early Internet period), with indicators for the age-cohorts, a_{ic} .³⁸ The vector $\mathbf{X}_{ic}$ contains the individual-level control variables from Equation (1) and μ_c are country fixed effects. Due to the inclusion of country fixed effects, the main effect of fixed-line diffusion (pertaining to the omitted age cohort, 55–65 years) on ICT skills (first stage) or wages (second stage) is not identified. ϑ_{ic} is the error term of the first-stage equation.³⁹

Note that in Equation (2) we effectively combine the IV estimation with a difference-in-differences strategy that exploits only age-induced variation within countries.⁴⁰ This approach addresses two major concerns. First, it captures any direct positive economic effect of the traditional fixed-line infrastructure on current wage levels. In fact, Roeller and Waverman (2001) show that a significant portion of economic growth in OECD countries between 1971 and 1990 can be attributed to telecommunications. Second, our approach controls for a potential correlation of baseline fixed-line

³⁸ We also experimented with using quadratic, cubic, or quartic polynomials in age. However, none of these functional forms is flexible enough to capture the actual age pattern, as can be seen in Figure A-2.

³⁹ We report Huber-White heteroskedasticity-robust standard errors. Results are qualitatively similar with standard errors clustered at the country level.

⁴⁰ Note that the treatment in our difference-in-differences approach is the take-up intensity of broadband Internet, which we approximate by a person's age in the early years of broadband diffusion. As such, our approach is somewhat different from the standard difference-in-differences strategy with a fully exogenous treatment.

networks with baseline levels of wealth, technology, education, institutions, skills, and so forth, all of which may affect today’s wages.⁴¹

3.4 *Within-Germany Instrumental-Variable Model*

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

In general, differences in broadband diffusion across regions within a country are largely determined by the endogenous decisions of profit-maximizing telecommunication carriers, which are, in turn, influenced by demand factors such as income, education, and urbanization. Since these factors may also affect current wages, we exploit the fact that past a certain threshold in the distance between a household and its assigned MDF broadband is no longer feasible (see Section 3.2). Specifically, in West Germany, the general structure of the voice-telephony network dates back to the 1960s when the provision of telephone service was a state monopoly having the declared goal of providing universal telephone service to all German households.⁴² While all households connected to an MDF enjoyed the same quality voice-telephony services, only those households closer than 4,200 meters (2.6 miles) to their assigned MDF could gain access to broadband Internet when a DSLAM was installed.⁴³

⁴¹ Our difference-in-differences approach accounts only for omitted variables that are correlated with ICT test scores in the same way for workers of different ages within in a country. In Section 5.2, we address the concern that omitted variables may affect younger and older workers differently.

⁴² We ignore East Germany since we cannot rule out that location decisions for the MDFs in East Germany, which were made after Reunification in the 1990s, were partly determined by unobserved characteristics of the municipalities that are also correlated with individual wages (see Bauernschuster, 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.

⁴³ The threshold value of 4,200 meters is a consequence of the DSL provision policy of the German telecommunication carrier, Deutsche Telekom, which marketed DSL subscriptions at the lowest downstream data transfer rate of 384 kbit/s only if the line loss was less than 55 decibel (dB). Since the copper cables connecting a household with the MDF usually had a diameter of 0.4 mm, a line loss of 55dB was typically reached at about 4,200 meters. As the actual line loss depends on other factors as well, the 4,200-meter threshold is only a fuzzy threshold (Falck, Gold, and Heblich,

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 3). 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.⁴⁴

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

Over time, many countries expanded ICT infrastructure to their so-called white spots, which are predominantly rural municipalities that would remain underprovided if left to market forces. Today, most countries have achieved a basic provision of broadband Internet to almost all households. Figure 7 shows the share of households with access to DSL between 2005 and 2009 in municipalities below and above the 4,200-meter threshold.⁴⁵ The figure reveals that about 30 percent of the initial difference in DSL availability was eliminated after this four-year period. Similar to our cross-country specification, variation in broadband Internet availability thus mainly comes from the early years of the Internet era.

<< Figure 7 about here >>

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.

⁴⁴ 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).

⁴⁵ Availability of DSL is measured as the percentage of households in a municipality for which DSL is technologically feasible. Data are from the German Broadband Atlas, commissioned by the German Federal Ministry of Economics, in which telecommunication operators self-report the number of households covered by their networks at a minimum downstream data transfer rate of 384 kbit/s. Consistent data on DSL availability at the municipality level are available only for this short time period.

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

$$ICT_{im} = \alpha_0 + \alpha_1 T_m + \mathbf{X}_{im} \alpha_2 + \mathbf{X}_m \alpha_3 + \vartheta_{im}. \quad (3)$$

The vector $\mathbf{X}_{im}$ includes a quadratic polynomial in work experience and gender.⁴⁶ Since we cannot include municipality fixed effects in this specification, the vector $\mathbf{X}_m$ contains controls for a municipality's economic situation prior to emergence of broadband by including municipality-level unemployment rate and the local age structure, both measured in 1999 (broadband first emerged in 2000 in Germany).⁴⁷ ϑ_{im} is the error term.⁴⁸

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

⁴⁶ This specification follows the baseline model in Hanushek, Schwerdt, Wiederhold, and Woessmann (2015). In Section 6, we report results when replacing work experience by age. Results are also similar when we use age cohort dummies as in the international analysis (results available upon request).

⁴⁷ 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 *ArGIS*.

⁴⁸ As the threshold instrument varies only across municipalities, standard errors in the within-Germany analysis are clustered at the municipality level (Moulton, 1986, 1990).

4. Returns to ICT Skills

4.1 *International Evidence*

We now estimate the causal effect of ICT skills on individuals' wages. Columns (3) and (4) of Table 1 present the results from our cross-country IV model. In the lower panel of Table 1, we report the first-stage coefficients and the F statistic on the excluded instruments.⁴⁹ The instruments turn out to be strong predictors of ICT skills. In the specification with country fixed-effects serving as our baseline (Column (4)), the Cragg-Donald F statistic is 28.5 and thus well above the critical value of 9.1. Thus, weak instrument bias is not a worry in this context. The first-stage estimates indicate a distinct age pattern in the effect of exogenous broadband availability on ICT skills. Compared to the effect for persons aged 55–65 years (the omitted category), an increase in the voice-telephony penetration rate from 0 to 100 percent leads to a 0.38 SD larger increase in the ICT skills of 20–34 year olds, a 0.84 SD larger increase for 35–44 year olds, and a 0.25 SD (albeit insignificantly) larger increase for 45–54 year olds.⁵⁰ Note, however, that the penetration rate (as percentage of the population) of fixed-line networks in 1996 varies only between 17 percent (Poland) and 68 percent (Sweden).

The upper panel of Table 1 shows the corresponding second-stage results. Across specifications, our results indicate significant returns to ICT skills. In our baseline specification in Column (4), the ICT skill coefficient of 0.236 implies that a one SD increase in ICT skills attributable to a historically larger fixed-line network leads to a 23.6 percent increase in wages. Returns are very similar when we leave out country fixed effects and instead include the main effect of fixed-line diffusion to capture omitted variables that are correlated with ICT skills in the same way for all age groups within a country (Column (3)).

<< Table 1 about here >>

⁴⁹ Stock and Yogo (2005) characterize instruments as weak not only when they lead to biased IV results but also when hypothesis tests of IV parameters suffer from severe size distortions. The authors propose values of the Cragg-Donald (1993) minimum eigenvalue statistic for which a Wald test at the 5 percent level will have an actual rejection rate of no more than 10 percent. We report these critical values and the Cragg-Donald F statistic at the bottom of Table 1.

⁵⁰ Complete first-stage results can be found in Table A-2.

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

Since our identification comes from an inverted-U-shaped age pattern in the effect of early broadband availability on ICT skills, we aim to identify the complier population by studying this age pattern for different subgroups of surveyed individuals. Following the returns to schooling literature which suggests that widely-used instruments for schooling differently affect individuals at different education levels (e.g., Kling, 2001), we explore potential differences in the age pattern of early broadband access for different levels of ICT proficiency.⁵¹ The OECD distinguishes three different ICT-proficiency levels: low (level 1 and below), intermediate (level 2), and high (level 3) (OECD, 2013a). In simple linear probability models, we find a pronounced inverted-U-shaped age pattern in the effect of early broadband availability on having an intermediate level of ICT proficiency, while there is no strong age pattern for high ICT proficiency (see Figure A-3).⁵² OLS regressions show that the complier population has particularly high returns to ICT skills (see Table A-3, Column 1).⁵³

As a benchmark to assess the magnitude of the estimated effect, note that one SD in ICT skills is roughly twice the learning progress made by school-attending PIAAC respondents between lower secondary and upper secondary education, which amounts to 20 PIAAC points across the countries

⁵¹ We did not find pronounced differences in the age pattern for different levels of educational attainment. See also Table 7 below.

⁵² Accordingly, the age pattern for low ICT proficiency is U-shaped.

⁵³ A potential reason for these high returns is occupational selection. We will come back to this issue in Section 7.

participating in the study.⁵⁴ Likewise, our estimated returns to ICT skills can be interpreted as follows: if an average worker in the United States (with ICT skills of 285 points) increased her ICT skills to the level of an average worker in Japan (299 points), her wages would increase by about 8 percent; this is close to the well-identified estimates on the returns to one additional year of schooling in developed countries.⁵⁵ It is also useful to compare the returns to ICT skills with existing estimates on returns to cognitive skills in other domains. In their sample of prime-age, full-time employed workers, Hanushek, Schwerdt, Wiederhold, and Woessmann (2015) find, in a specification comparable to ours, returns of 17.8 percent for a one SD increase in numeracy skills (see pooled model in their Table 2); returns are very similar for literacy skills.⁵⁶ Although their estimates cannot be interpreted causally, this is at least suggestive evidence that ICT skills as measured in PIAAC are somewhat more valued in the labor market than more traditional cognitive skills.⁵⁷

4.2 *Within-Germany Evidence*

Thus far, we have provided evidence on the wage returns to ICT skills from a cross-country IV model. We now zoom in on a single country—Germany—where we exploit historical peculiarities in the voice-telephony network as a source of plausibly exogenous variation in ICT skills. In Columns (5)–(8) of Table 2, we present results from IV regressions using as instrument a dummy variable that equals 1 for municipalities with distances between the municipality centroid and the assigned MDF above the threshold of 4,200 meters. In the full sample, shown in Columns (5) and (6), the first-stage results indicate that persons in municipalities above the 4,200-meter threshold have substantially lower

⁵⁴ 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.

⁵⁵ 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 labor, 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 (2016) for reviews.

⁵⁶ The returns to skills estimates are almost unchanged when we re-estimate their model for the 19 countries in our sample.

⁵⁷ The estimates in Table 1 are interpreted as individual (or private) returns to ICT skills; however, 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 labor force. Unfortunately, we cannot assess whether there are social returns to ICT skills because this would require instrumenting for both individual-level and aggregate ICT skills (see the discussion in Acemoglu and Angrist, 1999).

ICT skills than persons living in municipalities below the threshold, which is in accordance with the proposed learning-by-doing channel. In the specification with all controls in Column (6), we find that persons in municipalities with a distant MDF have 0.37 SD lower ICT skills than persons in municipalities with a close MDF.⁵⁸ When we use the threshold instrument in a sample of less-agglomerated West German municipalities without an own MDF (Columns (7) and (8)), the magnitude of the threshold estimate increases. Although the threshold instrument has a sizable effect on individual ICT skills, point estimates are somewhat imprecise. A major reason for the relatively low instrument strength is that people are mobile between municipalities, and yet we observe their municipality of residence only at the time of the PIAAC survey in 2011/2012.⁵⁹ Although we do not find evidence that the mobility pattern is systematically related to our instrument (see Section 5.3), it is a source of measurement error decreasing instrument strength.⁶⁰

Turning to the second stage of our IV estimation in the upper panel of Table 2, we find that a one SD increase in ICT skills attributable to the technical threshold in broadband availability increases wages by 30.6 percent in the full sample (Column (6)) and by 52.1 percent in the restricted sample (Column (8)). These estimates exceed the returns found in the international analysis, which is consistent with the evidence in Hanushek, Schwerdt, Wiederhold, and Woessmann (2015) that Germany has some of the highest returns to cognitive skills worldwide.⁶¹ Estimated returns in the IV models are about twice as large as in the corresponding OLS specifications, shown in Columns (1)–(4), which again indicates attenuation bias due to measurement error and an interpretation of our IV estimates as local average treatment effects (LATE).⁶²

<< Table 2 about here >>

⁵⁸ Table A-4 provides the complete first-stage results.

⁵⁹ Cragg-Donald Wald statistics are no longer valid with clustered standard errors. We therefore report the Kleibergen-Paap F statistic at the bottom of Table 2 to judge instrument strength.

⁶⁰ To address a potential weak instrument problem (e.g., Bound, Jaeger, and Baker 1995), we construct the Anderson and Rubin (AR) 95 percent confidence intervals, which are robust to weak instruments (Anderson and Rubin, 1949). The AR confidence intervals are quite similar to those obtained in the IV estimates, suggesting that our estimates do not suffer from a weak instrument problem that meaningfully biases the IV results (results available upon request).

⁶¹ 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).

⁶² Since the instrument varies only at the municipality level, the OLS results are based on variables aggregated at the municipality level, which provides the correct comparison with IV. One municipality-level SD in ICT skills amounts to 21 PIAAC points, which is half an individual-level SD.

5. Assessing the Identification Strategy

5.1 Placebo Tests: Other Skill Domains and First-Generation Immigrants

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

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

Table 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 preexisting fixed-line network in our baseline sample of natives and second generation immigrants (Columns (1) and (2)).⁶³ However, there is still an inverted-U-shaped age pattern in the effect of the traditional fixed-line network on ICT skills when controlling for numeracy and literacy skills (Column (3)). Arguably, controlling for ICT skills is problematic because the instruments affect ICT skills, making it an endogenous variable in the numeracy and literacy regressions. However, results are very similar when we net out the effect of ICT

⁶³ As long as we do not control for ICT skills, the instruments show a similar (although less pronounced) age pattern for numeracy and literacy skills as for ICT skills, reflecting the high correlation between the different skill domains. Since the instruments lose predictive power for numeracy and literacy once we include ICT skills, preexisting fixed-line diffusion affects numeracy and literacy skills only through ICT skills.

skills on numeracy and literacy skills ex ante by using residualized skill scores (Columns (4) and (5)), and we continue to find a distinct age pattern for residualized ICT skills (Column (6)). These results indicate that our instruments capture the “right” variation and increase confidence that the returns to ICT skills estimates discussed above are not biased due to unobserved skills of PIAAC respondents.

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

<< Table 3 about here >>

Within-Germany Analysis. We also need to ensure that our within-Germany specification isolates the effect of ICT skills on wages from the effect of general ability, as we have done above for the international sample. Table 4 presents the analogous placebo tests for the German sample. While neither numeracy nor literacy skills are systematically affected by the threshold instrument, the relationship between ICT skills and the instrument has the expected negative sign even conditional on the other skill domains. Table 5 shows that the threshold dummy does not affect the ICT skills of first-generation immigrants, who are unlikely to have acquired ICT skills in Germany.

<< Tables 4 and 5 about here >>

5.2 Exclusion Restriction: Potential Direct Wage Effects of Broadband

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

A major concern is that broadband is directly productive for firms, affecting wages of workers irrespective of their own usage of ICT skills. One way to account for these direct productivity effects of broadband is to control for alternative broadband access technologies which did not induce learning-by-doing effects in ICT skills. As noted in Czernich et al. (2011), broadband rollout is also determined by the spread of the cable TV network before broadband was introduced. However, preexisting cable TV diffusion should not exhibit learning-by-doing effects of a substantive magnitude due to a direct “distraction effect” from watching TV. For instance, data from American Time Use Survey reveal that in 2003 the average American spent 2.58 hours per day in front of the TV but only spent 0.08 hours per day on the phone. Therefore, the direct distraction effect of the cable TV network is likely far higher than that of voice telephony. In line with this reasoning, we find no significant age pattern in the effect of traditional cable TV diffusion on ICT skills (see first stage in Column (2) of Table 6). Controlling for a potential age pattern in direct productivity effects of broadband induced by traditional cable TV networks in Column (2) also barely changes the baseline returns to ICT skills (shown in Column (1)).

In Section 3.3., we also argued that new technologies like mobile Internet through 3G or, more recently, 4G reduced the reliance on fixed-line broadband technologies to access the Internet and build up ICT skills. We further argued that if mobile technologies are primarily used by younger persons, it may partly explain why we observe relatively small effects of exogenous fixed-line broadband diffusion on the ICT skills of persons in the younger age cohorts in PIAAC. Column (3) of Table 6 shows that the effect of mobile telephone diffusion⁶⁴ on ICT skills indeed decreases steadily in age, with ICT skills of persons aged 20–34 benefitting by far the most from mobile Internet

⁶⁴ The diffusion of mobile telephones has mainly enabled the provision of wireless broadband services (OECD, 2013b). Data on mobile telephone diffusion refer to 2012 to allow for learning-by-doing effects of wireless broadband access to materialize (4G was commercially introduced only in December 2009).

access.⁶⁵ Controlling for direct wage effects of broadband through mobile access technologies reduces estimated returns to ICT skills, but returns remain statistically significant and sizeable. This also holds when we simultaneously include preexisting cable TV diffusion and mobile telephone diffusion (Column (4)).

<< Table 6 about here >>

Moreover, based on available evidence, broadband Internet seems to have, at best, small positive wage effects on average. For instance, Kolko (2012) finds that broadband expansion did not affect average wages in U.S. ZIP code areas between 1999 and 2006. Similarly, Forman, Goldfarb, and Greenstein (2012) find that advanced Internet technology and wage growth were generally unrelated in the USA in the period 1995–2000. These findings for the United States are corroborated by Falck, Gold, and Heblich (2014) for Germany in the period 2004–2008 and by Poy and Schueller (2016) for Northern Italy in the period 2008–2013. However, while average wages seem to be unaffected by the availability of broadband Internet, Akerman, Gaarder, and Mogstad (2015) document a skill bias in wage effects of broadband Internet. The authors study the skill complementarity of broadband Internet using the expansion of broadband infrastructure in Norway in the 2000s as a natural experiment. They find that firms’ access to broadband Internet raises (lowers) wages of skilled (unskilled) workers.

In Table 7, we divide our sample into low-skilled (below tertiary education) and high-skilled (with tertiary education) workers. We restrict the sample to workers aged 30 years or more to ensure that we do not misclassify workers because they had not yet finished their university education. In this restricted sample, the average wage increase resulting from a one SD increase in ICT skills is 18 percent (Column (1)). This effect is mainly driven by high-skilled individuals, who have estimated returns of about 22 percent (Column (2)); returns for low-skilled workers are only 11 percent and not

⁶⁵ Note that the inverted-U-shaped age pattern in the effect of fixed-line networks on ICT skills becomes even more pronounced when age effects in mobile Internet access are accounted for.

statistically significant (Column (3)).⁶⁶ Thus, consistent with the evidence in Akerman, Gaarder, and Mogstad (2015), we find larger returns to ICT skills for high-skilled workers.

Such skill bias in the effect of broadband Internet would also raise concern if the share of high-skilled individuals varied across age cohorts. Indeed, the share of high-skilled individuals is larger among younger age cohorts than among older age cohorts in most PIAAC countries, reflecting the expansion of tertiary education in many countries in recent years.⁶⁷ To address this issue, we reweight individuals in our sample so that the share of high-skilled individuals is the same in each age cohort within a country. The results of this exercise are shown in Column (4) of Table 7. Estimated returns (23 percent) are somewhat larger than the baseline estimate using the original PIAAC weights (18 percent), and are very similar to the returns of workers with a university degree (22 percent).

In Column (5), we return to the sample of workers aged 20–65 and add a control variable for the percentage of persons completing tertiary education by country and age cohort. This variable reflects variations in the quality of the labor force over time, which may also affect the market returns to (ICT) skills. The aggregate composition of the labor force has the expected negative sign, suggesting that a larger share of individuals completing university education indicates lower selectivity of that educational type (Hanushek et al., 2016). However, estimated returns to ICT skills are qualitatively the same as in the baseline specification (Column (4) in Table 1).⁶⁸

<< Table 7 about here >>

The above evidence notwithstanding, there is additional reason to believe that potential direct productivity and wage effects are unlikely to bias our returns to ICT skills estimates. Figure 5 revealed

⁶⁶ Given the heterogeneity in the returns to ICT skills by educational degree, one potential concern in the within-Germany analysis is that the share of university-educated workers differs systematically between areas above and below the 4,200-meter threshold. It is therefore reassuring that the threshold instrument is not significantly associated with the share of university-educated workers in a municipality, either in the full sample or in the no own MDF sample (results available upon request).

⁶⁷ The difference in the share of university graduates between the youngest age group (30–34) and the oldest age group (55–65) is most pronounced in Ireland (31 pp.), the United Kingdom (19 pp.), Denmark (15 pp.), Korea (15 pp.), and Sweden (15 pp.). However, in Austria, Estonia, the Slovak Republic, and the United States, the share of university graduates is even larger in the oldest age group than in the youngest group.

⁶⁸ We obtain very similar results in the sample of employees aged 30–65 years.

that preexisting fixed-line networks are a good predictor of early broadband Internet penetration but do not well explain contemporaneous diffusion. In other words, our instruments induce variation in ICT skills that stems more from early differences than from contemporaneous differences in broadband penetration. Therefore, direct productivity and wage effects from contemporaneous broadband Internet use in firms should be unrelated to our instruments.

It would also be a threat to our identification strategy if online job search improved job matching, rendering workers more productive. However, although online job markets were introduced during the early phase of broadband diffusion, they were not widely used in the period 2000–2012. Employing annual household survey data from the German Socio-Economic Panel (SOEP) (Wagner, Frick, and Schupp 2007), we observe that the share of persons who found a job through the Internet ranges from only 1 percent in 2000 to 17 percent in 2012 (see Figure 8). For comparison, the share of persons who found a job through personal contacts is above 30 percent throughout this period, making it by far the most important job search channel.⁶⁹ Furthermore, it is reassuring for our cross-country IV strategy that the use of online job search channels does not systematically vary with age. Figure 8 shows that job search follows very similar patterns for our four age cohorts. Even among the 20–34-year olds, who appear to be the most frequent users of the Internet for job search, personal contacts are by far the most important channel.⁷⁰ In addition, Kuhn and Mansour (2014) point out that successful online job search does not lead to higher wages than traditional job search methods.

<< Figure 8 about here >>

However, although, on average, there may be no direct effect of broadband availability on wages through improved job matching, online job search may lead to higher wages for some age groups (e.g., younger workers). We test for age effects in the relationship between online job search and wage

⁶⁹ It could be argued that the contribution of the Internet to successful job search is in fact larger than suggested by the above figures because it may be used to contact friends, acquaintances and relatives about jobs. However, while we cannot explore this further with our data, Kuhn and Mansour (2014) find that only 20 percent of people who contacted friends and relatives to find their new job used the Internet to do so.

⁷⁰ It could be argued that the importance of online job search is attenuated in the data because part of the population has no access to fast Internet. However, Internet penetration in Germany was already at 76 percent in 2012 (Initiative D21, 2012), implying a much higher potential for online job search than the actually observed use.

growth between jobs by again employing the SOEP data. We construct a sample of individuals with job-to-job transition(s) between 2000 and 2012 who were aged 20–65 years in the year they reported a job change. The variable of interest is a binary variable that equals 1 if the respondent found her new job through Internet job search, and 0 otherwise. Depending on the specification, this variable is interacted with age cohort dummies. Following Kuhn and Mansour (2014), we control for gender, marriage status, an interaction of gender and marriage status, educational attainment, and migration status. Results are shown in Table 8. In Columns (1) and (2), the dependent variable is the log wage of the respondent’s current job, and we control for the wage in the previous year, as proposed by Kuhn and Mansour (2014).⁷¹ Consistent with previous results, we detect no significant relationship between Internet job search and wage growth on average (Column (1)). However, this relationship does not exhibit any age pattern either; in Column (2), the main effect of Internet job search and all interactions with age cohorts are small and insignificant. The same holds when we use a direct measure of wage growth between jobs as the dependent variable in Columns (3) and (4).⁷² Overall, there is no evidence in support of either an average effect or an age-dependent effect of Internet job search on wage growth.

<< Table 8 about here >>

5.3 *Sorting: Selective Internal Migration*

In our within-Germany IV model, one of the key threats to identification is that people selectively relocate from dwellings at a distance to the MDF above the 4,200-meter threshold to dwellings below the threshold. To empirically assess this concern, we first draw on data from the German regional statistics that contain information for the universe of West German municipalities

⁷¹ Potentially, wages in the previous year might already refer to the new job because in the SOEP individuals are asked whether they found a new job since December 31 two years prior to the survey year. However, results are similar to those reported below when we repeat the analysis using the wage two years before the job change to proxy the previous wage. Results are also similar when we use information on the month of job change to drop those workers who reported the same job change in two consecutive SOEP surveys. However, we refrain from doing so in the main analysis because the reported month of job change is likely to entail a considerable degree of measurement error.

⁷² Wage growth is calculated as the difference between the log of the hourly wage in the year individuals reported having undergone a job-to-job transition and the log of the hourly wage in the year before. Hourly wages are calculated as proposed in Brenke (2012), that is, gross monthly wage divided by the usual weekly working hours*4.2.

($n > 8000$) in the period 2001–2012. We calculate the annual out-migration rate for each municipality as the number of inhabitants moving out of a municipality in a given year relative to the municipality’s total population.⁷³ Using a pooled regression with only year dummies and a threshold indicator as regressors, we find that the average out-migration rate between 2001 and 2012 is 5.9 percent in municipalities below the threshold.⁷⁴ The coefficient on the threshold dummy is very small at -0.07 percentage points and negative, implying an out-migration rate in above-threshold municipalities of 5.8 percent. Due to the large sample size, the threshold coefficient is statistically significant at the 10 percent level. Regressions for each individual year show that the threshold coefficient is always negligible in economic terms, being statistically significant only in the years 2001–2005. Thus, results consistently show that people are not systematically leaving areas where broadband Internet is technologically not available.

We complement this municipality-level analysis by again employing annual household survey data from the SOEP, which allow us to identify moves at a very granular regional level (including moves within the same neighborhood). We use the exact geo-coordinates of the SOEP households in West Germany for the survey waves 2000–2010 to calculate whether a household has changed its distance to the MDF between two survey waves.⁷⁵ In our sample, we can follow 14,568 households for at least two consecutive waves and over an average period of 6.1 years. Among these households, 996 (6.8 percent) lived in a dwelling situated above the threshold in at least one survey wave. Overall, we observe 6,449 relocations in our sample. From a simple individual fixed-effects regression with a relocation dummy as outcome variable and the lagged threshold dummy as the only explanatory variable, we derive an average relocation rate of 7.3 percent (6.2 percent) for households from dwellings situated below (above) the threshold; the difference between both location rates is not statistically significant. Thus, corroborating the results from the municipality-level analysis, the average relocation rate of above-threshold households is again somewhat lower than that of below-threshold households. Furthermore, 93.8 percent of the relocations do not involve crossing the threshold.

In summary, the out-migration patterns employing either the German regional statistics or the SOEP are remarkably similar (out-migration rates of 5.9/5.8 percent vs. 7.3/6.2 percent), although both datasets contain observations at different levels of aggregation. Reassuringly, both analyses

⁷³ We use *ArGIS* to account for territorial changes between 2001 and 2012.

⁷⁴ As in our wage analysis, the threshold dummy is a binary variable taking the value 1 if a municipality is above the 4,200-meter threshold and 0 otherwise.

⁷⁵ The geo-coordinates of the SOEP households are confidential and available only onsite at the DIW in Berlin.

indicate that sorting related to broadband Internet access is unlikely to be a threat to our identification strategy.

6. Robustness

International Analysis. We now assess the robustness of our estimates to additional controls and changes in the sample. In Tables 9 and 10, we augment the baseline specification (Column (4) of Table 1) with controls for several pre-broadband variables interacted with the age cohorts. These variables are likely to affect today’s wage levels, but including them should not affect our main results if the exclusion restriction of our instruments holds. In Table 9, we include variables capturing a country’s general technology affinity (i.e., share of high-tech exports and share of STEM graduates), specialization in ICT products (i.e., ICT goods trade as a share of total trade), and technological composition of industries (i.e., industry computer use).⁷⁶ In Table 10, we consider pre-broadband economic indicators (i.e., average years of schooling, population size, and GDP per capita).⁷⁷ Reassuringly, the estimated returns to ICT skills remain significant and sizeable throughout all specifications.

The age cohort dummies included in the baseline model control for general age effects in earnings. However, our estimates would be biased if there are country-specific age effects in earnings that are correlated with the preexisting fixed-line networks. In Columns (5) and (6) of Table 10, we additionally include country-specific age trends (linear or/and quadratic) to account for unobserved age effects in earnings. In these regressions, we identify effects using only deviations from the country-level mean age trends in earnings. Estimated returns to ICT skills even increase in these highly demanding specifications. This evidence contributes to the discussion of potential direct productivity effects of broadband Internet in Section 5.2 because it makes even less likely the

⁷⁶ Since the sample changes between models due to data availability, we report returns to ICT skills from the baseline specification in the respective sample at the bottom of Table 9.

⁷⁷ All outcomes refer to 1996 unless otherwise noted. Data on ICT goods trade, STEM graduates, and GDP per capita are provided by the OECD. Data on high-technology exports are from the World Bank. Data on industry-level computer use are taken from Autor, Levy, and Murnane (2003) and are recoded to the ISIC industry classification (data refer to 1997). Data on years of schooling and population are from Barro and Lee (2010) and refer to 1995.

confounding stories of why access to the Internet could give rise to higher relative wages for younger workers irrespective of their ICT skills.⁷⁸

<< Tables 9 and 10 about here >>

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

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

International Analysis and Within-Germany Analysis. In Tables A-6 and A-7, we present robustness checks designed to test the sensitivity of our main results to adding further controls at the individual level. If our identification strategy addresses omitted-variable bias in the estimation of skill returns,

⁷⁸ If country-specific age effects would be a first-order concern, the residuals from the baseline regression would systematically deviate from a normal distribution. Figure A-4 plots the quantiles of the residuals against the quantiles of the normal distribution. The residuals are strikingly close to a normal distribution in all countries, again refuting the claim that our results can be attributed to the country-specific age structure in earnings.

adding other variables that are important for wage determination should leave the estimated IV coefficient on ICT skills unaffected. We add control variables that differently account for the tenure-earnings relationship (i.e., quadratic polynomial in actual work experience in the international analysis and quadratic polynomial in age in the within-Germany analysis), an indicator of full-time employment, and an indicator for whether a respondent is a native or a second-generation immigrant. Reassuringly, the estimated returns to ICT skills remain very similar when including these additional controls, providing evidence that our IV strategy does indeed identify variation in ICT skills that is independent of potentially omitted variables at the individual level.

Finally, we also assess the robustness of our results when assigning people with missing ICT skills a very low value of ICT skills (e.g., zero ICT skills; minimum ICT skills either of all respondents or of the respondents in the same country; one percent of the median observed ICT skills in a country). To take into account that ICT skills can be missing for different reasons, we also estimated specifications in which persons who reported to have no computer experience or who failed an initial short computer test were assigned zero ICT skills and persons who refused to take part in the computer-based assessment were assigned different percentiles (25th, 50th, 75th) of the country-specific ICT skill distribution. Returns to ICT skills tend to increase in these more inclusive samples, which is hardly surprising given that people without ICT skills information often work in low-paying jobs. Moreover, our sample comprises only employed workers, which introduces potential complications due to endogenous selection into employment. One way to take the employment effects of skills into account in our wage regression is to include the non-employed in the sample and assign them a very low log wage value (we use one percent of the median observed wage in a country). In such a model, estimated returns to skills increase from our baseline estimate of 0.236 to 0.432.⁷⁹

7. Mechanisms: Job Task Content and Occupational Selection

In this section, we investigate a potential driver of the positive wage returns to ICT skills, namely, that individuals with high ICT skills sort into jobs that are dominated by abstract tasks and pay wage premia. This is in line with the idea that recent technological change amplifies the comparative

⁷⁹ Detailed results for these extended samples are available upon request.

advantage of those workers engaged in nonroutine abstract tasks.⁸⁰ Specifically, Autor, Levy, and Murnane (2003) relate changes in the U.S. labor structure since the 1960s to the proliferation of computers in the workplace.⁸¹ The authors ask what kind of tasks computers execute that substitute for or complement tasks performed by workers. Therefore, instead of using conventional labor group distinctions (low-skilled, medium-skilled, and high-skilled; production and nonproduction; or blue-collar and white-collar), they propose a measurement of tasks that provides an intuitive and testable explanation of the relationship between the introduction of new technologies and the demand for heterogeneous labor. The basic idea is that computers substitute for routine tasks (those that can be accomplished by following explicit rules) and are complementary to nonroutine abstract tasks (such as problem solving, adaptability, and creativity).⁸² The underlying reasoning is that routine tasks embody explicit knowledge that can be relatively easily programmed, which is not the case for abstract tasks. Moreover, an increase in the supply of codifiable tasks increases the marginal productivity of employees who engage extensively in abstract tasks and who use routine work output as their work input.⁸³

The increasing importance of abstract tasks may be a driver of our result that ICT skills are considerably rewarded in modern labor markets. If high ICT skills are required to obtain jobs that are pervasive at abstract tasks because these tasks are complementary to computers, any wage premium attached to abstract jobs would imply positive returns to ICT skills. To analyze whether occupational selection is an avenue through which ICT skills lead to higher wages, we estimate our baseline IV models replacing hourly wages with the occupational task content. For this analysis, we gained access from the OECD to the two-digit ISCO-08 (International Standard Classification of Occupations) codes for all employed PIAAC respondents. We link these occupational codes to the measures of

⁸⁰ 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 premia (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).

⁸¹ See Handel (2007) for a critical appraisal of the role played by computers in the increasing wage inequality in the United States.

⁸² Historically, however, technology has not always benefited skilled workers performing abstract tasks. For example, in the beginning of the 19th century, automated looms replaced skilled weavers in the textile industry with a punch card and a few unskilled workers. Moreover, implementation of the Fordist assembly line in the automobile industry in the early 20th century increased the demand for routine tasks. See also Goldin and Katz (1996, 2008).

⁸³ Recent evidence suggests that such skill complementarity of personal computers is also present in Europe (Akerman, Gaarder, and Mogstad, 2015).

abstract, routine, and manual tasks from Goos, Manning, and Salomons (2014).⁸⁴ Additionally, we also classify occupations by computer use by PIAAC respondents, that is, the frequency of using software, programming language, and spreadsheet tools at work.⁸⁵

Table 11 shows the results for the international sample; Table 12 provides the findings for the German analysis. Throughout specifications and samples, higher ICT skills increase the abstract task content of jobs and the intensity of computer use at work. At the same time, an increase in ICT skills decreases the routine and manual intensity of jobs.⁸⁶ The magnitudes of the effects are considerable: in the international analysis, a one SD increase in ICT skills leads to a 0.80 SD increase in the abstract intensity of a job (e.g., from a business and administration associate to a business and administration professional or from an assembler to a sales worker). Likewise, the routine task content of jobs decreases by 0.41 SD for a one SD increase in ICT skills (e.g., from a plant and machine operator to a science and engineering associate or from a laborer in mining, construction, and manufacturing to a health professional).

<<Tables 11 and 12 about here >>

To further explore the interpretation of our IV results as local average treatment effects (see Section 4.1), we show that the effect of ICT skills on the sorting into jobs with a high abstract and low

⁸⁴ They combine the five original Dictionary of Occupational Titles (DOT) task measures of Autor, Levy, and Murnane (2003) into three task aggregates: (nonroutine) abstract tasks, routine tasks, and (nonroutine) manual tasks (see also Akerman, 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 SD one across occupations. See Autor, Levy, and Murnane (2003, Appendix 1) for examples of workplace activities with different task intensities. Workers with the highest abstract job content in our sample are managers and teaching professionals. Occupations with the lowest abstract content are elementary occupations (e.g., cleaners and helpers).

⁸⁵ 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 $\bar{x}$ -score for each of the variables individually, aggregate the $\bar{x}$ -scores, and normalize by the SD of the aggregate. All calculations are performed for each country individually to account for possible differences in answering behavior.

⁸⁶ These estimates are not statistically significant in the full German sample.

routine/manual task content is mainly driven by individuals with intermediate ICT proficiency (Table A-3, Columns (2)-(4)). While individuals with high ICT proficiency (level 3) are most likely to work in abstract-intense jobs, further increases in their ICT skills do not contribute as much to an increase in the abstract intensity of jobs as is the case for workers with intermediate ICT proficiency. This suggests that crossing a certain ICT-skill threshold allows individuals to enter abstract-intense jobs.

A potential concern with this analysis is that the results may be driven by age-biased job reallocations, as highlighted by Autor and Dorn (2009). Specifically, young workers (with relatively high average ICT skills) may not yet have acquired much occupation-specific human capital and may develop new skills relatively easily, so they are more likely to manage transitions from routine to abstract jobs than are older workers (with relatively low average ICT skills). However, we do not observe a clear age pattern in any of the job tasks (see Figure A-5). If anything, individuals working in jobs that make intense use of abstract tasks or computers are relatively old and workers in jobs that are pervasive at routine or manual tasks are relatively young.

Our results show that the proliferation of computers is an important mechanism behind the positive returns to ICT skills in modern labor markets. Jobs that heavily involve abstract tasks pay substantial wage premia, as shown at the bottom of Tables 11 and 12, and having high ICT skills appears to be a prerequisite for obtaining these well-paid jobs. Employing back-of-the-envelope calculations, we can provide an idea of how much of the returns to ICT skills can be explained by occupational selection. In regressions of log hourly wages on abstract, routine, and manual task scores, and conditioning on age cohort dummies, female indicator, and country fixed effects, we find that a one SD increase in abstract task content is associated with a 21.3 percent increase in hourly wages, whereas a one SD increase in routine (manual) task content is associated with a 5.2 (2.1) percent increase (decrease) in wages. Multiplying the effect of ICT skills on the occupational task content by the task-wage associations gives: $0.803 \times 21.3 - 0.406 \times 5.2 - 0.343 \times (-2.1) = 15.7$. Based on this simple calculation, occupational selection explains about two-thirds ($15.7/23.6=0.665$) of the wage increase due to higher ICT skills in the international sample.

8. Conclusion

This paper investigates the labor-market returns to ICT skills in 19 developed economies using a novel dataset that contains direct measures of individuals' ICT skills. We identify exogenous variation

in ICT skills by exploiting technological peculiarities that determine broadband Internet availability across countries and German municipalities. The underlying idea is that ICT skills are developed through learning-by-doing, which is facilitated by Internet access. Our results indicate that better ICT skills are systematically related to higher wages: a one SD increase in ICT skills leads to an almost 24 percent increase in wages in the international sample and to an increase of 31 percent in the German sample. Placebo tests proving that the variables that exogenously determine Internet access cannot explain any variation in numeracy or literacy skills suggest that our IV models insulate the wage effect of ICT skills from that of general ability.

By showing that ICT skills are rewarded quite substantially in the labor market, our results support Neelie Kroes's notion of ICT skills as "the new literacy." Still, our findings do not provide conclusive evidence on how modern knowledge-based economies value ICT skills relative to other 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.

Our paper also contributes to the discussion over social inequality in access to the Internet, also known as the "digital divide." For instance, linking data from the 2013 American Community Survey with the most recent version of the National Broadband Map, President Obama's Council of Economic Advisors shows that black and Hispanic households in the United States are 16 and 11 percentage points, respectively, less likely to have an Internet connection than are white households (CEA, 2015). In a recent paper, Vigdor, Ladd, and Martinez (2014) argue that this digital divide is actually beneficial for disadvantaged groups because—based on available evidence—providing better access to technology would broaden even further the math and reading achievement gap between rich and poor. This conclusion, however, ignores the fact that the skills needed to master technology are substantially rewarded in today's labor market. In fact, structural and technological change will likely raise the demand for expertise in ICT-related tasks in the future.⁸⁷ The fundamental insight of this paper—that ICT skills can be promoted by providing access to ICT infrastructure—suggests that the

⁸⁷ 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 polarization of skill demand.

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.

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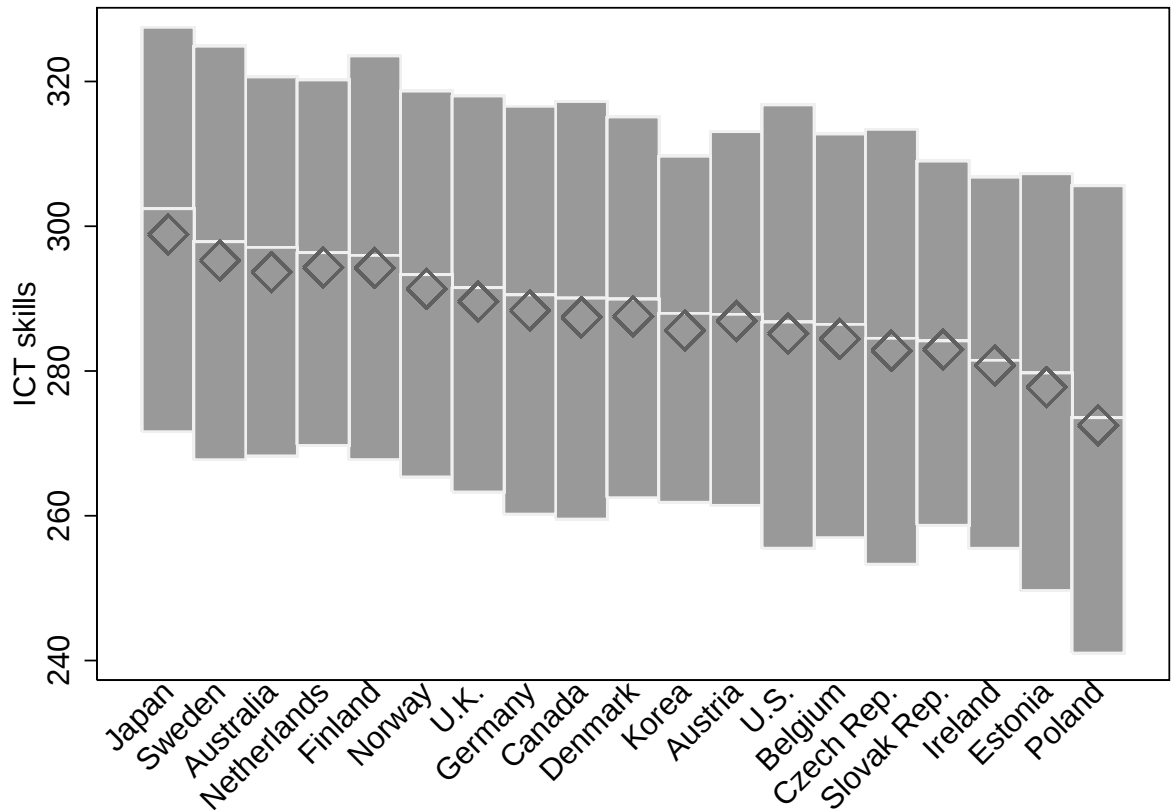
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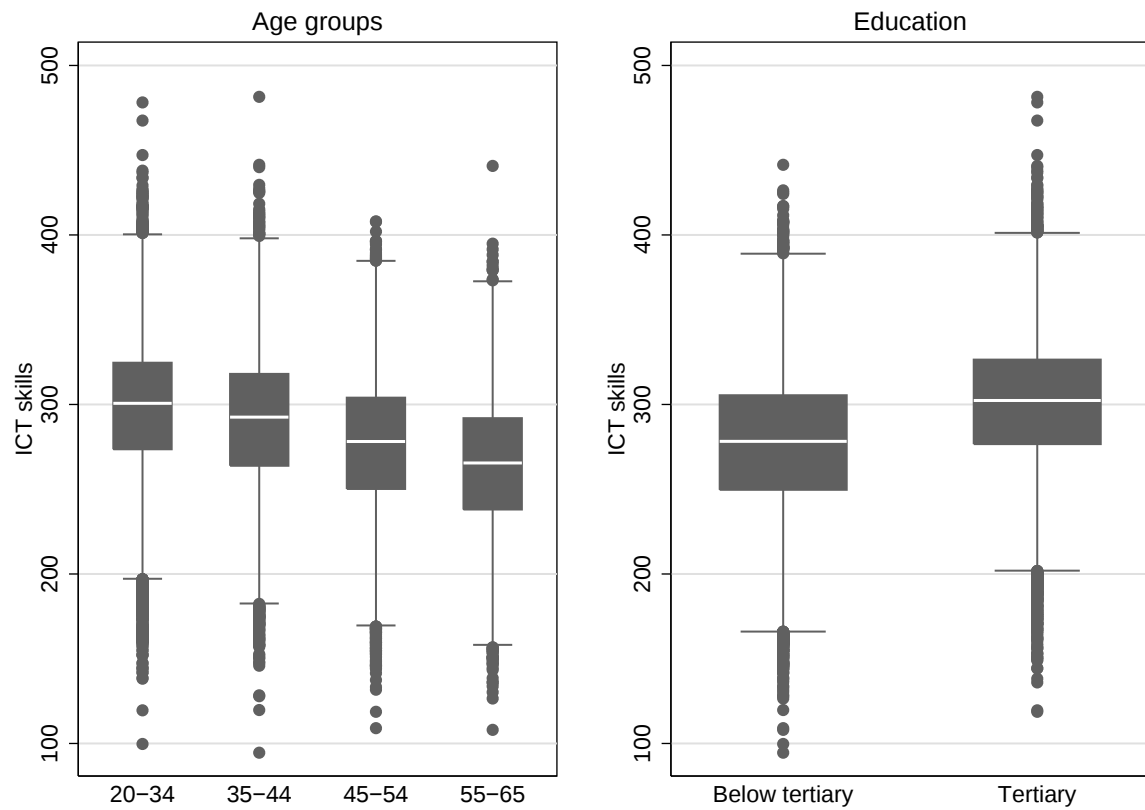
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Figure 1: ICT Skills Around the World



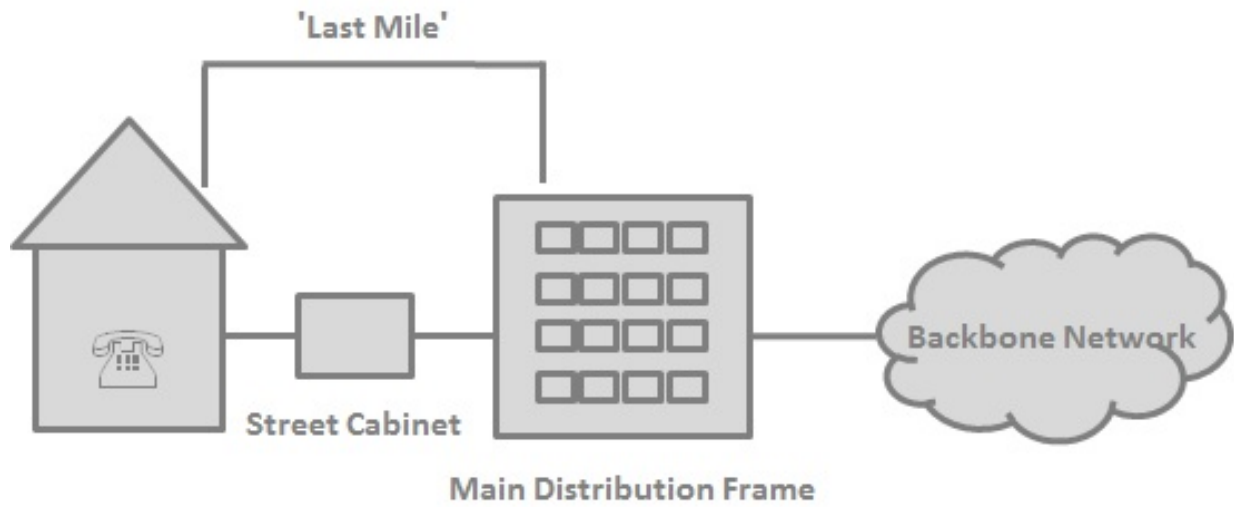
Notes: Graph shows ICT skills by country. White bars indicate median ICT skills, diamonds indicate mean ICT skills, and boxes indicate the 25th–75th percentile ICT skill range. Countries are ordered by median ICT skills. Sample: employees aged 20–65 years, no first-generation immigrants. *Data source:*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

Figure 2: ICT Skills by Age and Education



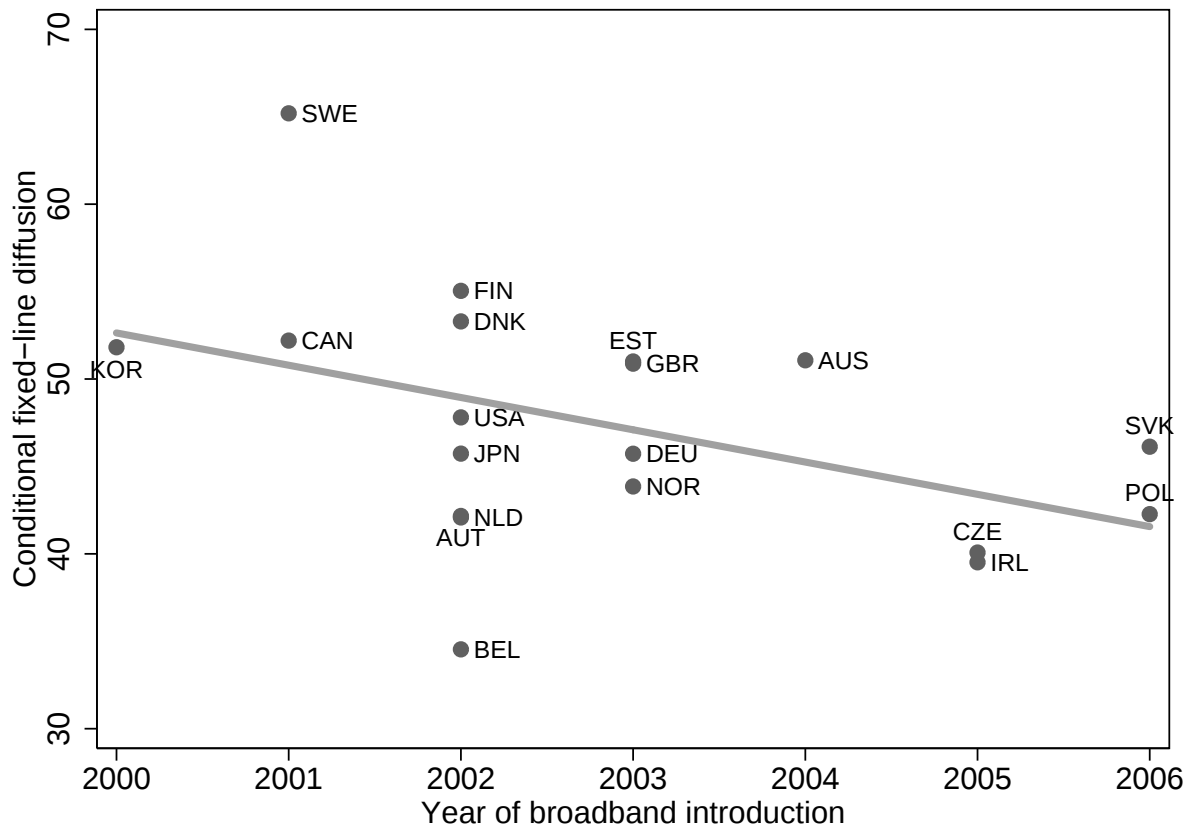
Notes: Graph shows box plots of ICT skills for indicated age groups and by educational attainment. Sample: employees aged 20–65 years, no first-generation immigrants. *Data source:* PIAAC.

Figure 3: The Structure of a DSL Network



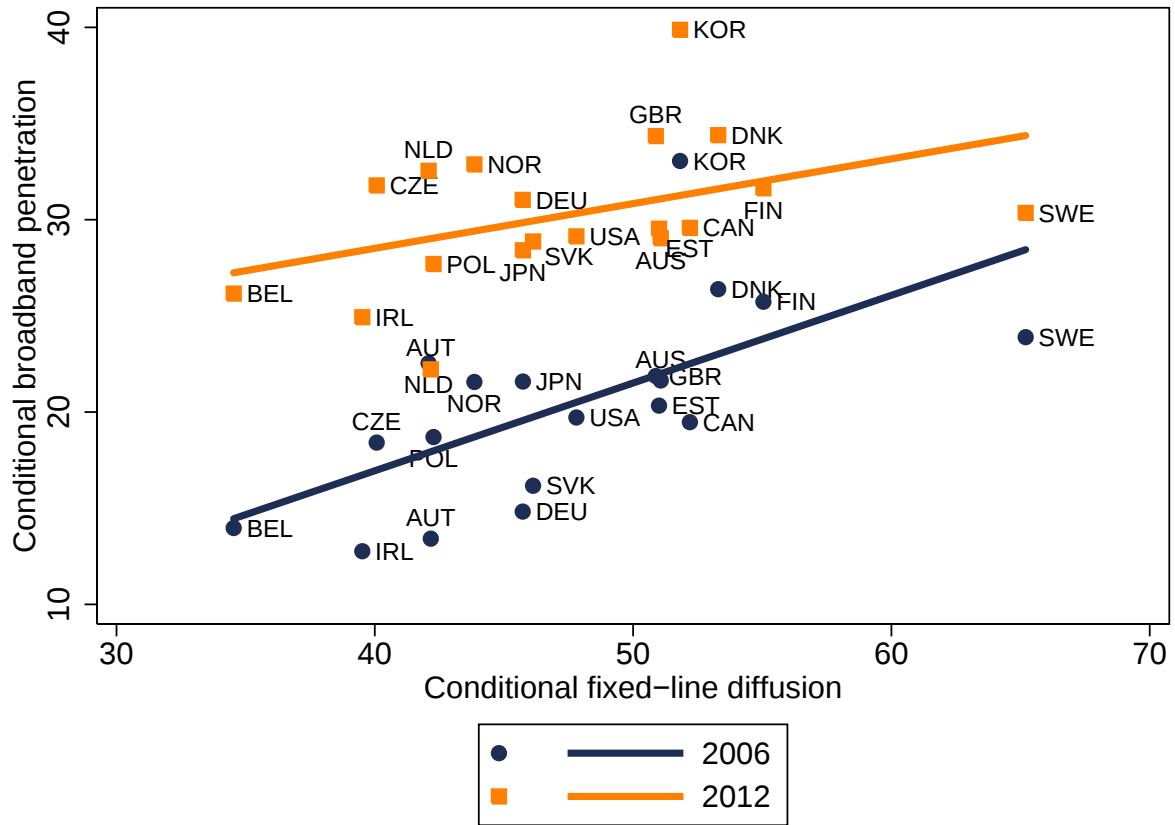
Notes: The figure shows the structure of a DSL network that relies on the “last mile” of the preexisting fixed-line voice-telephony network. The “last mile” consists of copper wires connecting every household via the street cabinet to the main distribution frame. At the main distribution frame, a DSLAM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

Figure 4: Effect of Fixed-Line Diffusion on Broadband Introduction



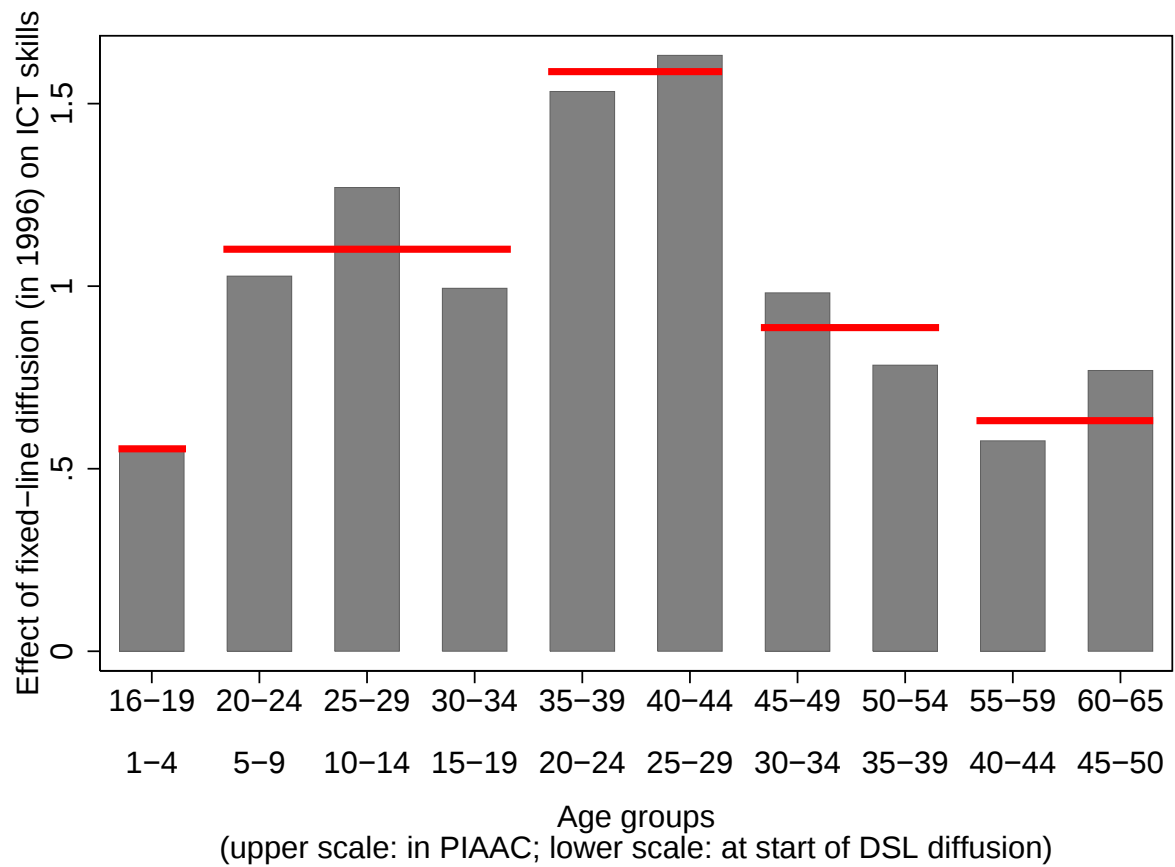
Notes: Graph shows the relationship between fixed-line diffusion in 1996 (conditional on control variables) and first emergence of broadband in a country. Fixed-line diffusion is the number of telephone access lines per inhabitant in 1996. Year of broadband introduction in this graph is the year when broadband penetration (i.e., the number of broadband subscriptions per inhabitant) first exceeded 5 percent. Control variables are GDP per capita in 1996 (in logs), years of schooling in 1995, population size in 1995, and cable TV diffusion (measured as cable television subscriptions per inhabitant) in 1996. *Data sources:* Barro and Lee (2010), ITU, OECD.

Figure 5: Effect of Fixed-Line Diffusion on Broadband Penetration: 2006 vs. 2012



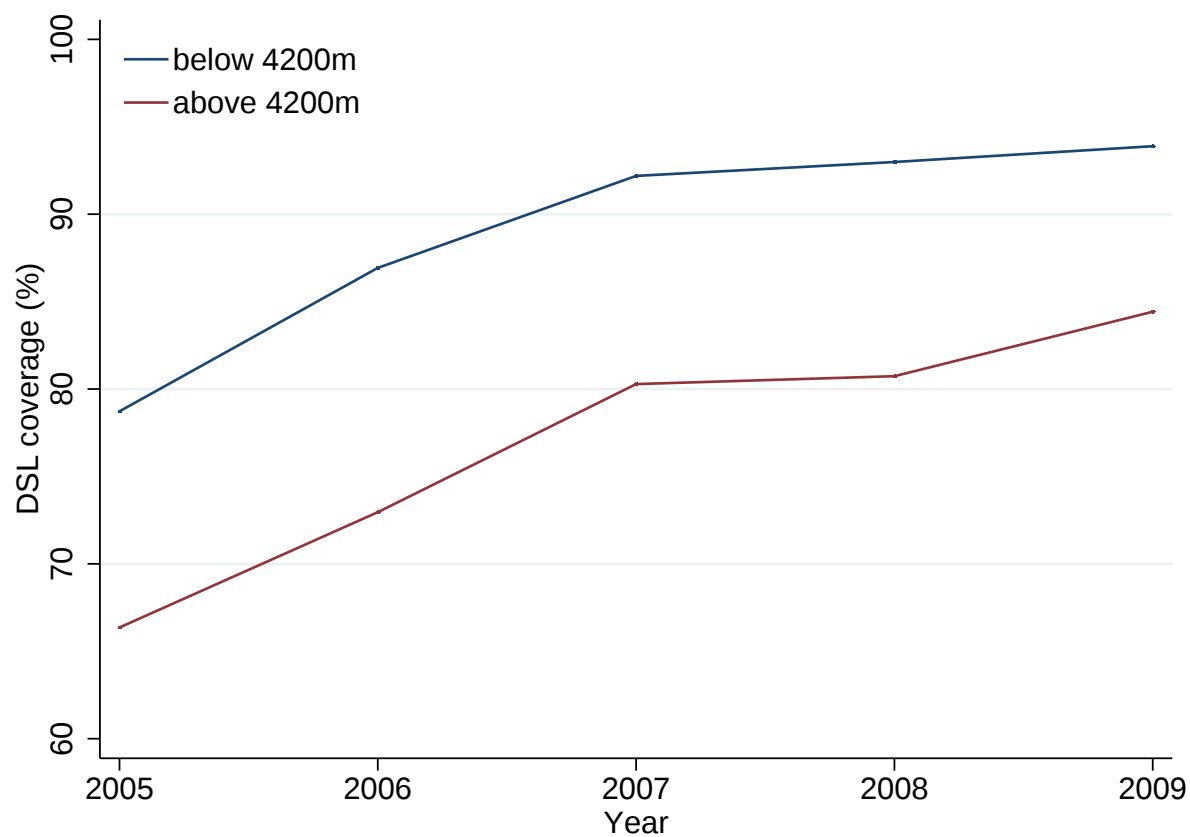
Notes: Graph shows country-level added-variable plots from regressing broadband penetration in 2006 (dark navy) or 2012 (orange) on fixed-line diffusion in 1996 and control variables. Broadband penetration is the number of broadband subscriptions per inhabitant. Fixed-line diffusion is the number of telephone access lines per inhabitant in 1996. Control variables are GDP per capita in 1996 (in logs), years of schooling in 1995, population size in 1995, and cable TV diffusion (measured as cable television subscriptions per inhabitant) in 1996. *Data sources:* Barro and Lee (2010), ITU, OECD.

Figure 6: Preexisting Fixed-Line Diffusion and ICT Skills by Age Group



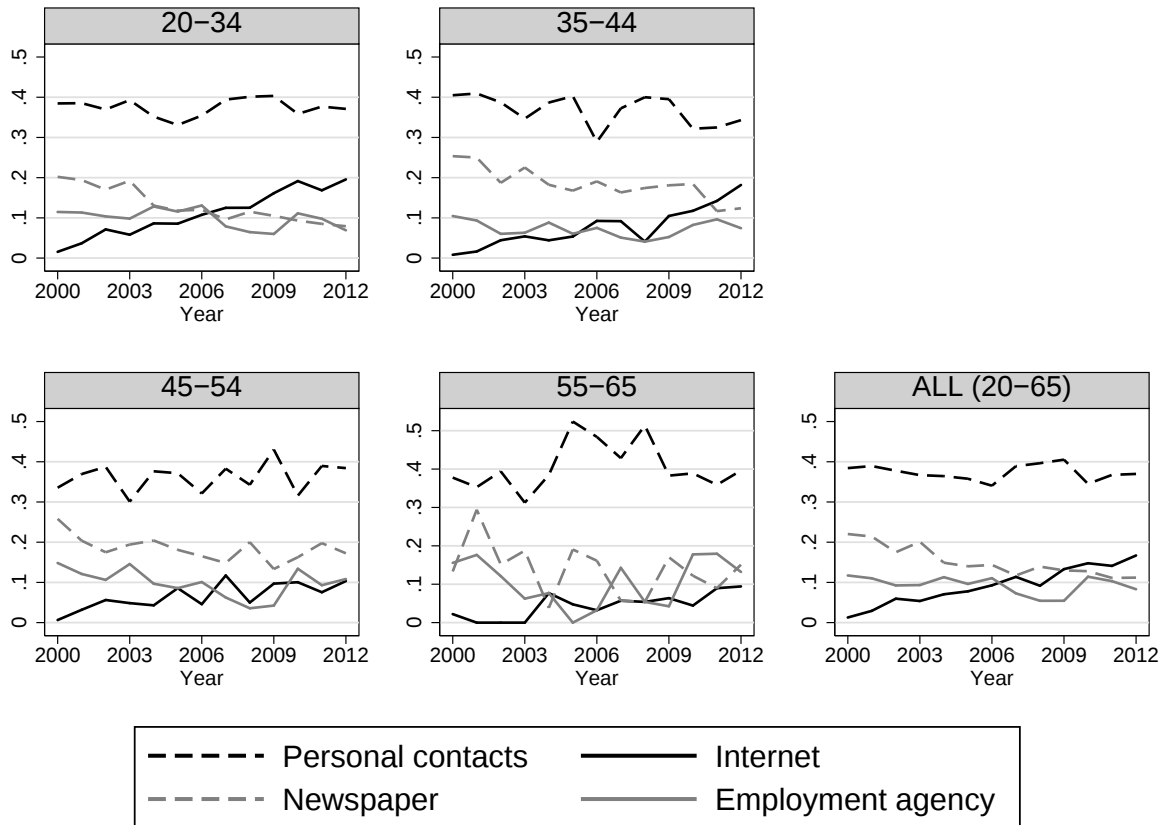
Notes: Coefficient estimates on fixed-line voice-telephony diffusion (in 1996) for indicated age groups in a regression of ICT skills (standardized to SD 1 across countries) on fixed-line diffusion. Regression weighted by sampling weights (giving same weight to each country). Sample: employees, no first-generation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

Figure 7: DSL Coverage in Above-Threshold and Below-Threshold Municipalities



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

Figure 8: Importance of Different Methods for Successful Job Search by Age Group



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

Table 1: Returns to ICT Skills: International Evidence

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

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

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

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

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

Table 3: International Evidence: Placebo Tests

Sample:	Natives & 2nd-gen. immigrants (baseline sample)						1st-gen. immigrants
Dependent variable:	Numeracy	Literacy	ICT	Numeracy (residualized)	Literacy (residualized)	ICT (residualized)	ICT
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Fixed-line diffusion $\times$ age 20–34	0.184* (0.099)	–0.125 (0.095)	0.141 (0.103)	0.190* (0.099)	–0.124 (0.095)	0.147 (0.103)	–0.789 (0.508)
Fixed-line diffusion $\times$ age 35–44	0.107 (0.103)	–0.063 (0.100)	0.313*** (0.108)	0.121 (0.103)	–0.060 (0.099)	0.305*** (0.108)	–0.865* (0.502)
Fixed-line diffusion $\times$ age 45–54	–0.029 (0.107)	–0.024 (0.103)	0.121 (0.110)	–0.024 (0.107)	–0.024 (0.102)	0.117 (0.110)	–0.571 (0.489)
ICT skills	0.675*** (0.004)	0.737*** (0.004)					
Numeracy skills			0.332*** (0.007)				
Literacy skills			0.549*** (0.007)				
Individual characteristics	X	X	X	X	X	X	X
Country fixed effects	X	X	X	X	X	X	X
R squared (adjusted)	0.58	0.63	0.67	0.10	0.04	0.10	0.09
Individuals	53,879	53,879	53,879	53,879	53,879	53,879	6,298

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

Table 4: Within-Germany Evidence: Placebo Tests Using Other Skill Domains

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

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

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

Table 5: Within-Germany Evidence: Placebo Tests Using Migration Status

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

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

Table 6: Alternative Broadband-Access Technologies

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

Notes: Two-stage least squares regressions weighted by sampling weights (giving same weight to each country). Sample: employees aged 20–65 years, no first-generation immigrants. Dependent variable in second stage is *log gross hourly wage*, measured in PPP-USD. *Fixed-line diffusion*: voice-telephony penetration rate (telephone access lines per inhabitant). *Cable TV diffusion*: cable television subscriptions per inhabitant. *Mobile diffusion*: mobile-cellular telephone subscriptions per inhabitant. Omitted age category is 55–65 years. Individual characteristics are age cohorts and gender. Robust standard errors in parentheses. Significance levels: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. *Data sources*: ITU, PIAAC.

Table 7: International Evidence: Accounting for the Different Educational Compositions Across Age Groups

Second stage (Dependent variable: log gross hourly wage)					
	Baseline	Tertiary education	Below tertiary education	Rewighted skill shares	Labor force composition
	(1)	(2)	(3)	(4)	(5)
ICT skills	0.184** (0.081)	0.219* (0.132)	0.106 (0.122)	0.227* (0.123)	0.165** (0.079)
Age 30–34	−0.255*** (0.071)	−0.333*** (0.113)	−0.187* (0.097)	−0.305*** (0.108)	−0.393*** (0.068)
Age 35–44	−0.155*** (0.055)	−0.187** (0.094)	−0.115 (0.074)	−0.187** (0.085)	−0.142*** (0.051)
Age 45–54	−0.069** (0.027)	−0.067 (0.048)	−0.055 (0.038)	−0.081* (0.042)	−0.062** (0.026)
Female	−0.173*** (0.013)	−0.138*** (0.038)	−0.217*** (0.015)	−0.164*** (0.019)	−0.156*** (0.010)
% with tertiary education, country-cohort					−0.035 (0.073)
Country fixed effects	X	X	X	X	X
First stage (Dependent variable: ICT skills)					
Fixed-line diffusion × age 30–34	0.283 (0.186)	−0.166 (0.248)	0.485* (0.254)	0.129 (0.209)	0.446*** (0.160)
Fixed-line diffusion × age 35–44	0.801*** (0.172)	0.405* (0.229)	0.814*** (0.236)	0.638*** (0.199)	0.836*** (0.168)
Fixed-line diffusion × age 45–54	0.234 (0.173)	−0.166 (0.236)	0.442* (0.234)	0.188 (0.205)	0.255 (0.170)
Cragg-Donald Wald F statistic	27.3	12.3	11.7	16.4	27.2
Stock&Yogo critical value	9.1	9.1	9.1	9.1	9.1
Individuals	40,480	20,396	20,084	40,480	53,879

Notes: Two-stage least squares regressions weighted by sampling weights (giving same weight to each country). Sample: employees aged 30–65 years (20–65 years in Column (5)), no first-generation immigrants. Dependent variable in second stage, *log gross hourly wage*, is measured in PPP-USD. Column (1) replicates the baseline model in Column (4) of Table 1. In Columns (2) and (3), we split the sample by college education. In Column (4), weights are adjusted such that in each country and age cohort, the share of persons with tertiary education equals the country-specific share in the age cohort 35–44 years (other age cohorts are 30–34 years, 45–54 years, and 55–65 years). In Column (5), we add the percentage completing university education in each country and age cohort (calculated from the PIAAC data). ICT skills are standardized to SD 1 across countries. *Fixed-line diffusion*: voice-telephony penetration rate (telephone access lines per inhabitant) in 1996. Omitted age category is 55–65 years. Robust standard errors in parentheses. Significance levels: * p<0.10, ** p<0.05, *** p<0.01. *Data sources*: ITU, PIAAC.

Table 8: Does Online Job Search Affect Wages?

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

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

Table 9: Further Country-Level Controls from the Pre-Broadband Era: Technology Indicators

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

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

Table 10: Further Country-Level Controls from the Pre-Broadband Era: Economic Indicators and Country-Specific Age Trends

Additional country control indicated in column heading						
	Years schooling	Population	GDP per capita	All		
	(1)	(2)	(3)	(4)	(5)	(6)
ICT skills	0.188** (0.073)	0.180** (0.074)	0.378*** (0.090)	0.401*** (0.097)	0.404*** (0.092)	0.375*** (0.123)
Country-specific linear trends					X	X
Country-specific quadratic trends						X
Individual characteristics	X	X	X	X	X	X
Country fixed effects	X	X	X	X	X	X
First stage (Dependent variable: ICT skills)						
Fixed-line diffusion $\times$ age 20–34	0.456*** (0.154)	0.593*** (0.157)	0.735*** (0.224)	0.692*** (0.223)	−0.098 (0.417)	0.215 (0.546)
Fixed-line diffusion $\times$ age 35–44	0.893*** (0.167)	0.964*** (0.170)	1.132*** (0.242)	1.054*** (0.241)	0.550* (0.285)	0.692 (0.454)
Fixed-line diffusion $\times$ age 45–54	0.284* (0.169)	0.398** (0.171)	0.363 (0.239)	0.306 (0.238)	0.096 (0.207)	0.126 (0.308)
Cragg-Donald Wald F statistic	30.8	30.3	16.9	15.2	26.6	13.9
Stock & Yogo critical value	9.1	9.1	9.1	9.1	9.1	9.1
Individuals	53,879	53,879	53,879	53,879	53,879	53,879

Notes: Two-stage least squares regressions weighted by sampling weights (giving same weight to each country). Sample: employees aged 20–65 years, no first-generation immigrants. Dependent variable in second stage is *log gross hourly wage*, measured in PPP-USD. Additional country controls refer to 1995 unless otherwise noted and are interacted with the following age cohorts: 20–34 years, 35–44 years, 45–54 years, and 55–65 years. *GDP per capita* in Column (3) is in logs and refers to 1996. Column (4) includes interactions with all country-level variables from Columns (1)–(3). Omitted age category is 55–65 years. Individual characteristics are age cohorts and gender. Robust standard errors in parentheses. Significance levels: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. *Data sources:* Barro and Lee (2010), ITU, PIAAC.

Table 11: Mechanisms: Occupational Selection (International Evidence)

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

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

Table 12: Mechanisms: Occupational Selection (Within-Germany Evidence)

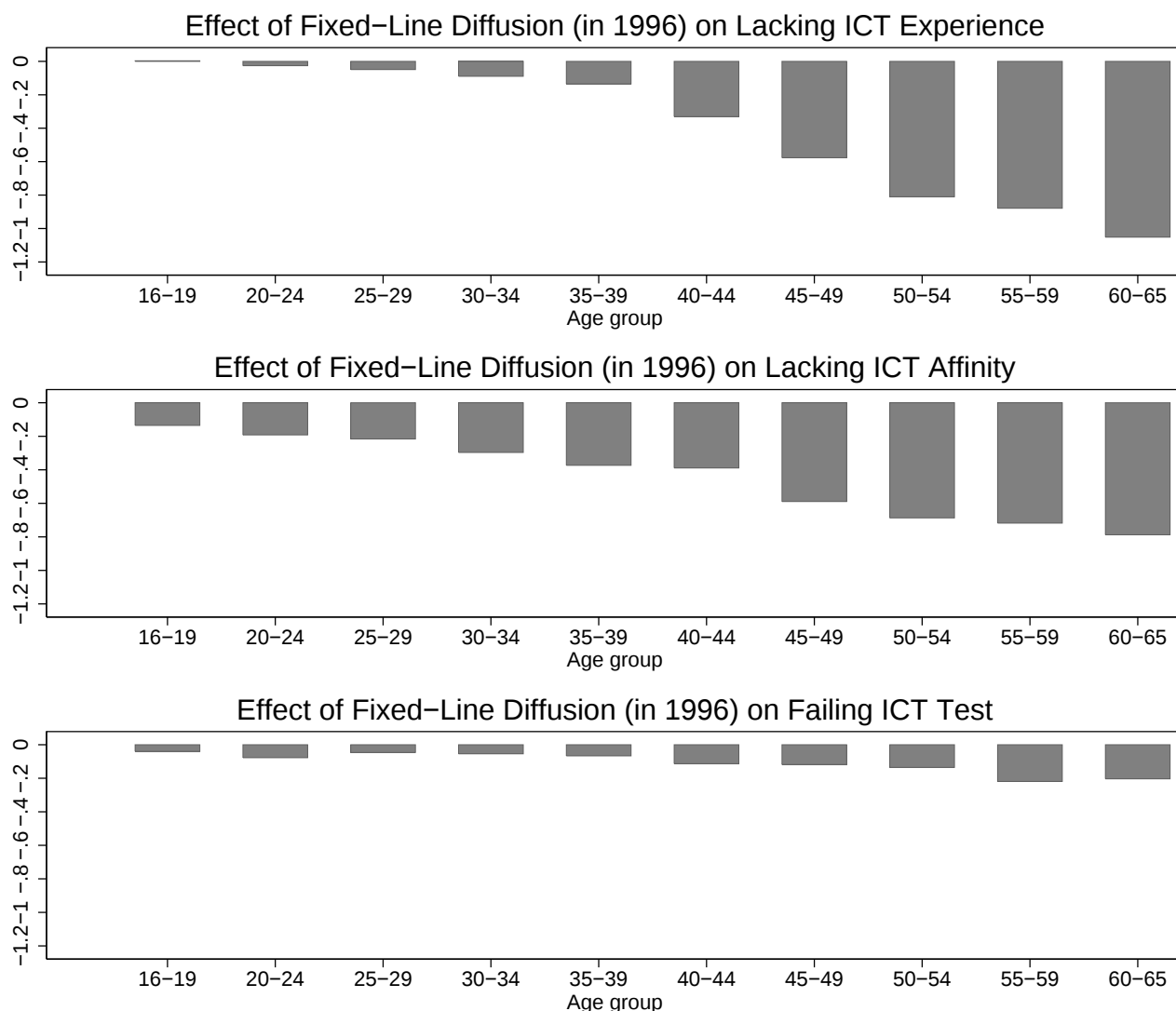
Second stage (Dependent variable: occupational task content)								
	Full sample				No own MDF sample			
	Abstract	Routine	Manual	Computer use	Abstract	Routine	Manual	Computer use
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
ICT skills	0.420*	0.346	-0.397	0.466***	0.989***	-0.454*	-0.637**	0.556***
	(0.236)	(0.220)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

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

* p<0.10, ** p<0.05, *** p<0.01. *Data sources:* German Broadband Atlas, German Federal Statistical Office, PIAAC.

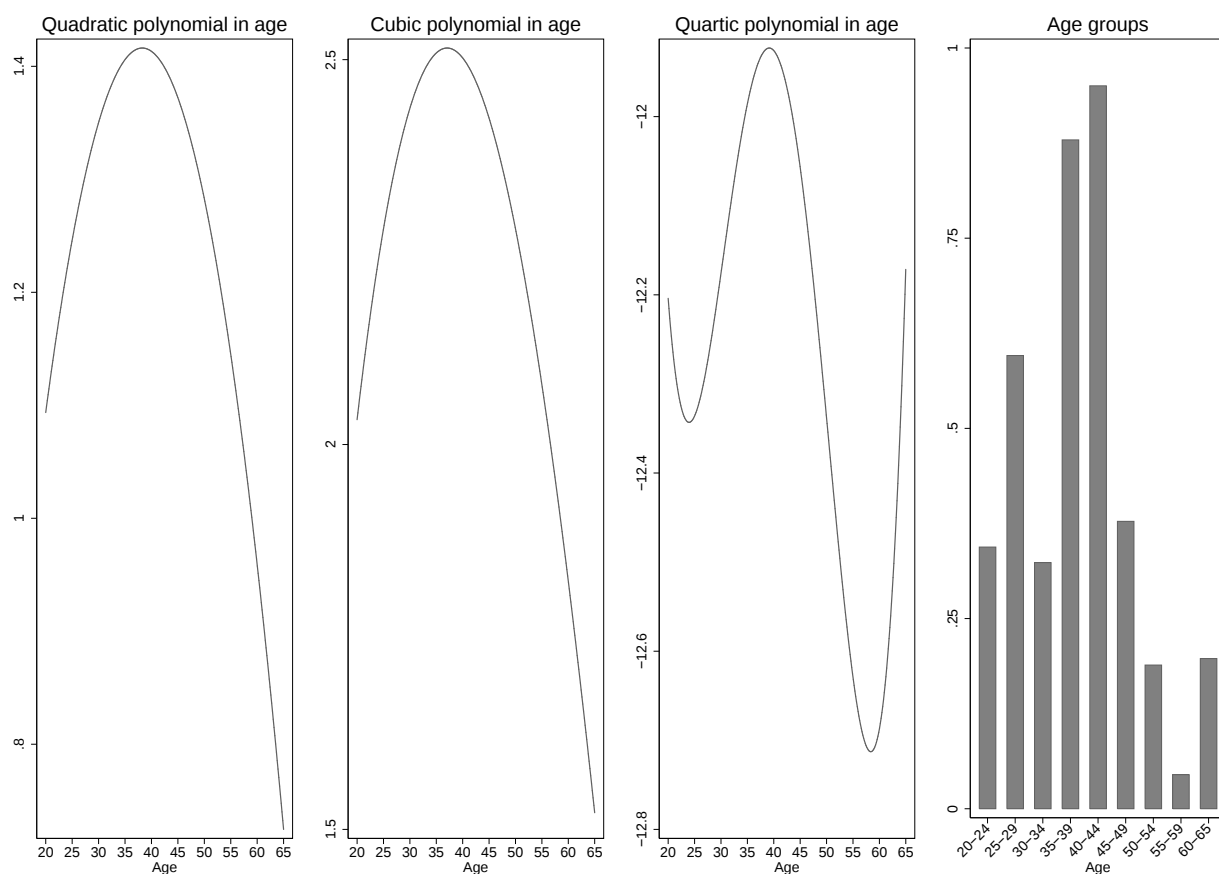
Appendix

Figure A-1: Preexisting Fixed-Line Diffusion and ICT Illiteracy by Age Group



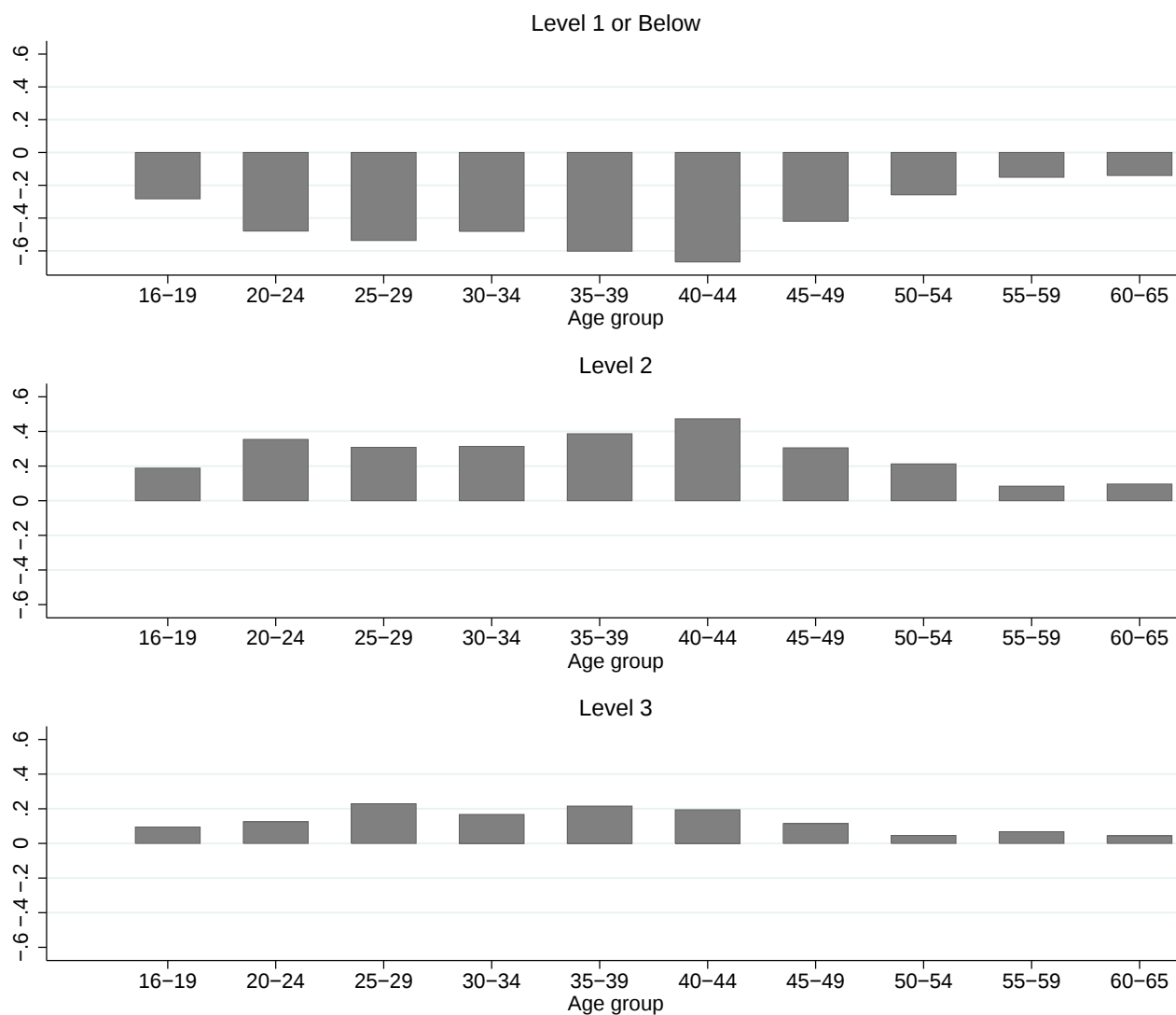
Notes: Coefficient estimates on fixed-line voice-telephony diffusion (in 1996) for indicated age groups in a regression of ICT illiteracy on fixed-line diffusion, by reason for ICT illiteracy. ICT skills can be missing in PIAAC due to lack of computer experience reported by the respondent (Panel A),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

Figure A-2: The Impact of Fixed-Line Diffusion on ICT Skills by Age: Functional Forms



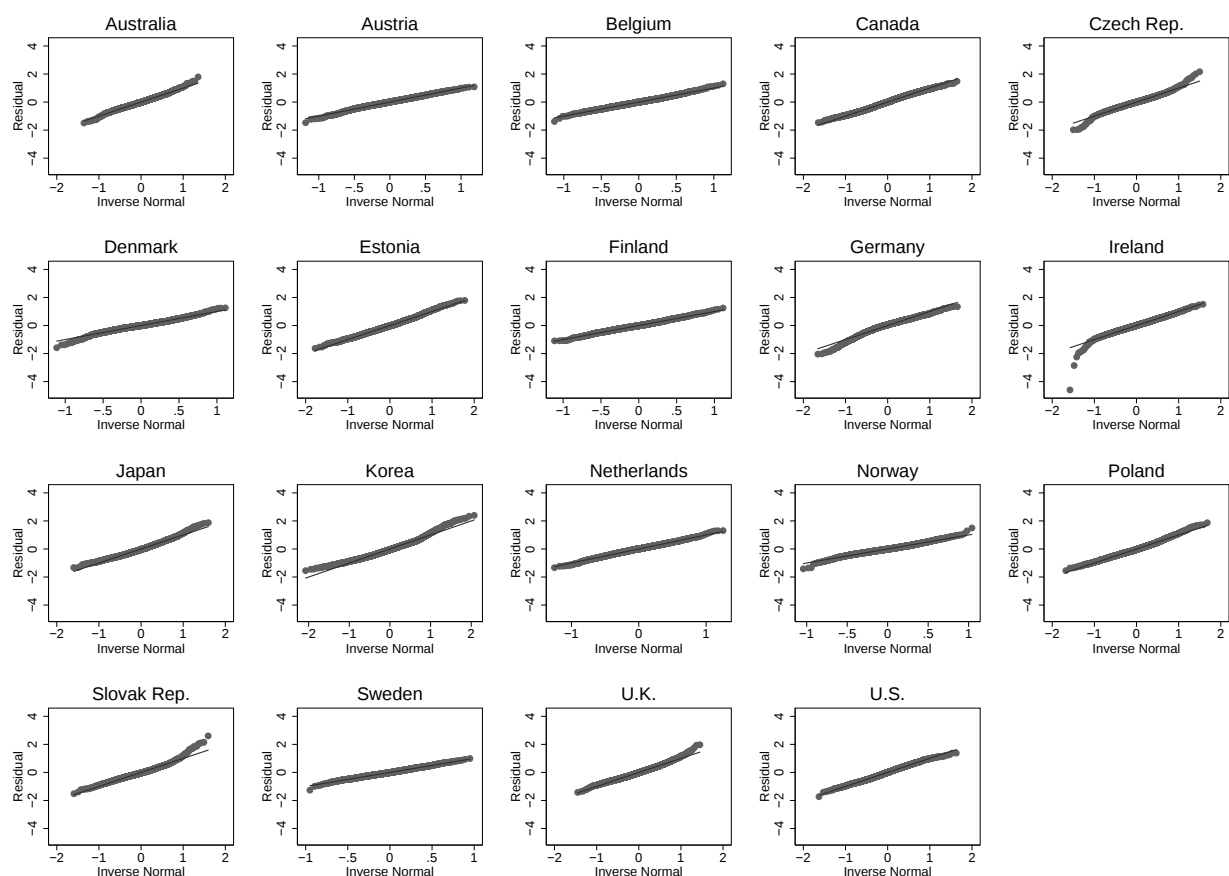
Notes: Coefficient estimates on fixed-line diffusion (in 1996) interacted with various functional forms of age (indicated in the panel heading) in a regression of ICT skills (standardized to SD 1 across countries) on fixed-line-diffusion-age interactions, respective age variables, gender, and country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

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



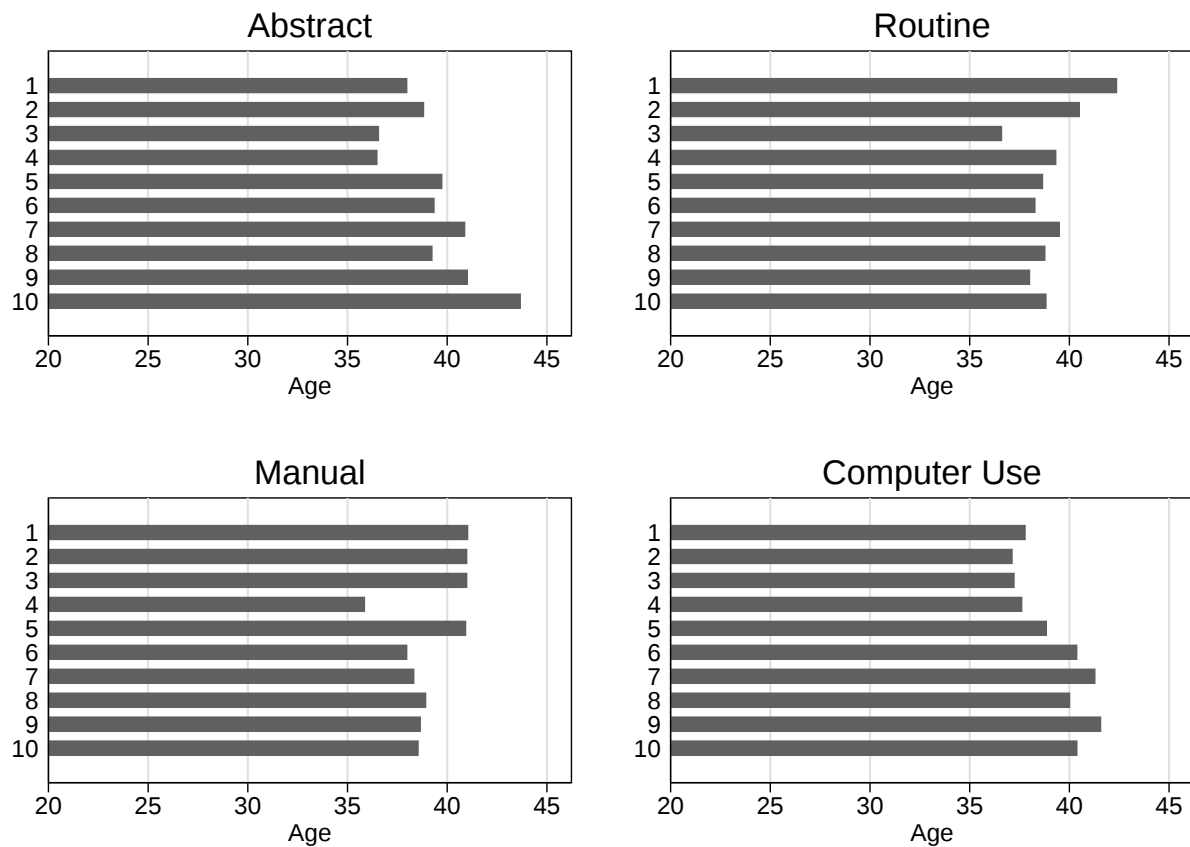
Notes: Coefficient estimates on fixed-line voice-telephony diffusion (in 1996) for indicated age groups in a regression of ICT proficiency on fixed-line diffusion. ICT proficiency is a binary variable indicating whether a person has the ICT proficiency level mentioned in the panel header, and 0 otherwise: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

Figure A-4: Q-Q Plots for Residuals of Baseline Model



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

Figure A-5: Age Composition of Job Tasks



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

Table A-1: Descriptive Statistics

	Pooled	Australia	Austria	Belgium	Canada	Czech R.	Denmark	Estonia	Finland	Germany
Gross hourly wage	18.0	19.2	17.0	20.3	20.7	9.2	24.3	10.4	18.8	19.2
(in PPP-USD)	(10.2)	(8.7)	(6.6)	(7.3)	(9.4)	(4.2)	(8.3)	(6.3)	(6.9)	(9.5)
ICT skills	287.3	293.7	286.9	284.4	287.4	282.8	287.6	277.8	294.3	288.4
	(41.3)	(37.5)	(37.1)	(41.6)	(42.8)	(44.1)	(40.2)	(41.7)	(41.3)	(41.4)
Numeracy skills	287.8	284.6	290.6	294.4	282.0	285.8	293.2	284.2	298.6	288.2
	(44.1)	(45.9)	(41.3)	(43.9)	(47.3)	(40.6)	(42.4)	(42.0)	(43.5)	(44.5)
Literacy skills	288.8	294.1	281.9	289.2	288.9	280.6	284.2	284.1	302.0	282.5
	(40.7)	(41.0)	(37.8)	(40.6)	(43.7)	(39.7)	(38.5)	(41.9)	(42.5)	(42.4)
Experience (years)	18.0	18.4	18.7	19.3	20.3	17.2	22.4	15.9	17.9	19.0
	(11.5)	(11.3)	(10.8)	(11.0)	(11.5)	(11.0)	(11.9)	(11.1)	(11.6)	(12.0)
Female (share)	0.49	0.49	0.50	0.48	0.49	0.44	0.50	0.56	0.52	0.48
Observations	53,879	2,533	2,061	2,267	10,499	1,959	3,296	2,626	2,770	2,517
	Ireland	Japan	Korea	Netherl.	Norway	Poland	Slovak R.	Sweden	U.K.	U.S.
Gross hourly wage	22.9	16.6	17.8	20.8	25.2	9.6	9.1	18.6	19.0	22.6
(in PPP-USD)	(11.7)	(10.7)	(14.2)	(8.9)	(8.7)	(5.5)	(6.3)	(5.3)	(11.2)	(13.1)
ICT skills	280.7	298.9	285.6	294.3	291.4	272.5	283.0	295.3	289.6	285.2
	(38.9)	(44.1)	(36.0)	(38.2)	(38.5)	(47.8)	(37.4)	(40.9)	(40.8)	(43.9)
Numeracy skills	274.6	301.6	278.6	294.1	295.8	276.4	292.8	296.2	282.5	273.1
	(44.9)	(40.3)	(37.1)	(42.3)	(44.0)	(43.6)	(37.9)	(43.2)	(46.2)	(49.6)
Literacy skills	283.2	306.0	283.8	297.9	291.5	281.0	285.2	295.5	288.0	287.1
	(41.6)	(35.5)	(35.0)	(40.5)	(38.9)	(42.3)	(33.6)	(38.9)	(42.5)	(43.4)
Experience (years)	16.7	17.2	11.6	19.0	19.8	13.1	16.0	19.9	19.8	20.7
	(10.2)	(10.8)	(8.8)	(11.1)	(11.5)	(10.4)	(10.7)	(12.6)	(11.5)	(12.0)
Female (share)	0.56	0.39	0.42	0.48	0.50	0.48	0.49	0.49	0.49	0.52
Observations	1,738	2,141	2,203	2,575	2,746	2,503	1,649	2,351	3,572	1,873

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

Table A-2: International Evidence: First Stage

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

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

Table A-3: Complier Analysis

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

Notes: Least squares regressions weighted by sampling weights (giving same weight to each country). Sample: employees aged 20–65 years, no first-generation immigrants (in Columns (2)–(4), individuals who did not provide information on their occupation are excluded). Dependent variable is the logarithm of gross hourly wage (in PPP-USD) in Column (1) and task measures taken from Goos, Manning, and Salomons (2014) in Columns (2)–(4). The abstract task measure is the average of two variables from the U.S. Dictionary of Occupational Titles (DOT): direction control and planning, measuring managerial and interactive tasks, and GED Math, measuring mathematical and formal reasoning requirements; the routine task measure is a simple average of two DOT variables, set limits, tolerances and standards, measuring an occupations demand for routine cognitive tasks, and finger dexterity, measuring an occupations use of routine motor tasks; and the manual task measure corresponds to the DOT variable measuring an occupations demand for eye-hand-foot coordination. The task measures are mapped onto the ISCO occupational classification system (two-digit level) and are normalized to have mean 0 and SD 1 across occupations (see also Table 11). *Level* refers to the level of ICT proficiency achieved by the individual: level 1 or below = less than 291 PIAAC points; level 2 = 291–340 points; level 3 = more than 340 points (OECD, 2013a). Omitted category is ICT-proficiency level 2. All regressions control for age cohorts, gender, country fixed effects, and interactions of the covariates with the ICT-proficiency level. ICT skills are standardized to SD 1 across countries. Robust standard errors in parentheses. Significance levels: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. *Data sources:* Goos, Manning, and Salomons (2014), ITU, PIAAC.

Table A-4: Within-Germany Evidence: First Stage

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

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

Table A-5: International Evidence: Other Age Samples

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

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

Table A-6: International Evidence: Further Individual-Level Controls

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

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

Table A-7: Within-Germany Evidence: Further Individual-Level Controls

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

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

B Measurement Error

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

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

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

where $\lambda = \frac{Var(ICT^*)}{Var(ICT^*) + Var(u)}$. The factor λ indicates how much the true effect β is attenuated and is often referred to as the reliability ratio or signal-to-noise ratio. Neffke (2016) shows that in this classical errors-in-variables model the estimated coefficient on ICT skills, $\hat{\beta}$, can be written as:

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

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

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

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

Bias adjustment using $Var(u)$. To back out a measure of $Var(u)$, we use information on ICT test reliability published in the Technical Report of PIAAC (OECD 2013c). Test reliability is computed by calculating how much variance in ICT skills is explained by the item responses and background factors included in the model to derive the skill values.¹ The reliability ratios were estimated for each country separately depending on the country-specific distributions for ICT skills (the procedure was similar for numeracy and literacy skills).² The country-specific reliability ratios range from 0.8 (in the Slovak Republic) to 0.89 (in Sweden), with a mean ratio of 0.85.³

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

Bias adjustment using different measures of ICT skills. Another way to correct for measurement error in the ICT-skills variable is to use multiple measures of ICT skills. Since we have both the answers and difficulty levels of all questions that were used to create the ICT-skill measure, we can split the assessment into two parts (each with the same average difficulty) and instrument ICT skills derived from one set of questions with ICT skills derived from the other set of questions. If

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

² See Chapter 18 in OECD (2013c) for details.

³ In psychometric test theory, it is often argued that Cronbach's α is a natural indicator of test reliability. This measure is a function of the number of test items and the covariances between all possible item pairs. For instance, Metzler and Woessmann (2012) and Bietenbeck, Piopiunik, and Wiederhold (2015) use Cronbach's α to correct for measurement error in tested teacher subject knowledge. While Cronbach's α is not reported for any skill domain in PIAAC, it is possible to construct the measure by using respondents' answers to all individual test items (using Stata's alpha command). The estimated reliability ratio is 0.83 for the full sample, and ranges between 0.78 and 0.85 when estimated for each country separately. Thus, the estimated Cronbach's α is very similar to the reliability ratios reported by the OECD.

measurement errors in both ICT-skill variables are uncorrelated, using one measure as an instrument for the other will remove part of the attenuation bias caused by measurement error.⁴

We first construct a sample of PIAAC participants that solved *all* ICT-related questions. As PIAAC also followed the common procedure in international assessment tests to administer different sets of items to different respondents, imposing this restriction reduces the sample to 8,791 respondents. We further divide the full set of questions into two parts, where each question in one set has a twin question in the other set with the same difficulty level. We then estimate respondents' ICT skills on the basis of each set of questions. Specifically, separately for each set of questions, we regress the original ICT-skill measure in PIAAC on each question (coded as binary variables taking a value of 1 if the answer was correct and 0 otherwise)⁵ and use the estimated coefficients to obtain predicted ICT skills.

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

Both adjustments address common concerns about test quality such as specific items on the ICT-skills test being a bad measure of skills relevant on the labor market. The results show that taking away this measurement error leads to a substantial increase in estimated returns, suggesting that attenuation bias may indeed be an important issue in the analysis of returns to ICT skills. Importantly, these adjustments still understate the amount of error in our ICT-skills measure, because measurement error

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

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

due the fact that test constructs developed in PIAAC may not be an encompassing measure of the underlying concept of ICT skills is not eliminated.

Additional References

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

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

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