Technology and Market Change – Economic Effects of ICT Infrastructure

Alexandra Heimisch

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Alexandra Heimisch

Referent: Prof. Dr. Oliver Falck
Korreferent: Prof. Dr. Simon Wiederhold
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Erstgutachter:	Prof. Dr. Oliver Falck
Zweitgutachter:	Prof. Dr. Simon Wiederhold
Drittgutachterin:	Prof. Dr. Monika Schnitzer
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Für meine Eltern &
in Erinnerung an meine Großeltern

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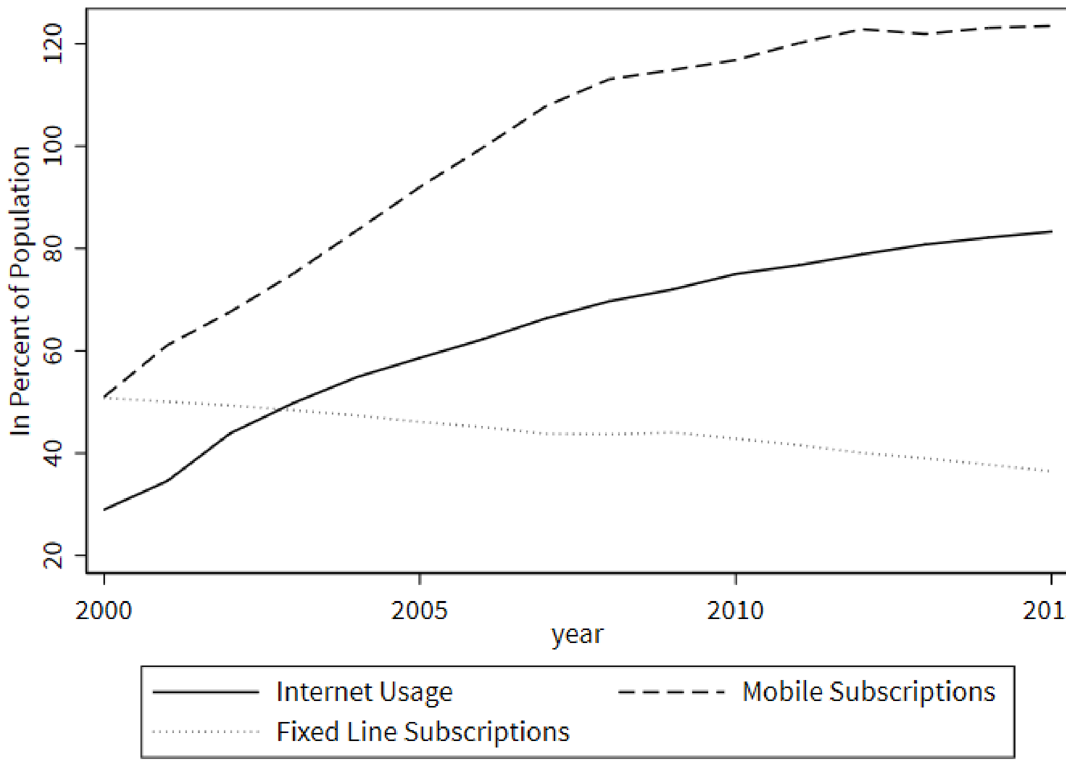
Setting the Stage: Technology as a Game Changer in Markets

Smartphones, robots, broadband Internet, ... Even though it sometimes seems like these new technologies have been around forever and we cannot do without them anymore, a few decades ago, they did not exist. Figure 0-1 supports the claim that those information and communication technologies (ICT) marched into our lives with waving flags. It shows Internet usage, mobile subscriptions and fixed-line subscriptions per 100 inhabitants for the average of 24 OECD countries, which together represent about 75 percent of worldwide GDP. While fixed-line telephony, as an established incumbent technology, is in steady decline, the usage of the Internet as well as mobile telephony increased substantially. Close to every person in the OECD uses the Internet and literally everybody, on average, has a mobile subscription. Some individuals even have two. Taking everything into account, it is a simple fact with a myriad of, still partly unforeseeable, consequences: New technologies are all around.

Their victory march was possible because ICT infrastructure shows huge potential in simplifying things by enhancing the (global) flow of information and decreasing the transaction costs of information handling. I will look at the friction reducing effect in *Chapter 3*, based on the example of employer-employee matching.

However, game changers like new technologies do not only simplify things, they also impose challenges which need to be met and create winners and losers. A loser, naturally, is older technology that is replaced by the new and "improved" version, as is also suggested by Figure 0-1 for the market for telecommunications. *Chapter 1* will analyze this matter in more detail. Despite that, winners and losers are created in other markets affected by new technologies as well, for example the labor market. Previous literature and *Chapter 2* show that the winners of new technologies work in jobs with a higher abstract task content. This is due to the fact that new technologies - computers and the Internet in particular - act as complements to these tasks, whereas they substitute for routine tasks, that can be programmed relatively easy (e.g. Autor, Levy, and Murnane, 2003; Akerman, Gaarder, and Mogstad, 2015).

Figure 0-1: New ICT Technology on the Rise



Notes: Graph shows mean of Internet usage, mobile subscriptions and fixed-line subscriptions per 100 inhabitants between 2000 and 2015 for 24 OECD countries: Australia, Austria, Belgium, 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, and the United States. *Data source:* International Telecommunications Union (ITU).

Along with the question of winners and losers goes the question of substitution effects, which have the power to create winners and losers. In the three chapters of this thesis I will investigate three dimensions of substitutability, brought about by new information and communication technologies. *Chapter 1* looks at in how far new technologies are able to crowd out an incumbent technology on the market for telecommunications. The *second chapter* deals with the new set of skills needed to master new technologies. These are becoming increasingly important in modern labor markets and have a wage return. In the course of this chapter it is shown that the wage returns stem from these new skills not being substitutes, but complements to computers. Computers are complements to abstract tasks, and jobs that involve many abstract tasks pay higher wages. New technologies and their platforms as a substitute for traditional information channels are dealt with in *Chapter 3* in the context of search frictions in the market for jobs.

However, through the course of this thesis, we will also see that, as in almost every game, winning and losing is sometimes determined by sheer luck or misfortune - or simply by the fact that the rules were made a long time ago, when nobody ever expected it to become a game. I take advantage of these circumstances econometrically to identify causal effects in *Chapter 2*. The idea is that individuals closer to (or living in countries with) better network infrastructure, initially designed for something else, are more likely to acquire the skills necessary to master new technologies via learning-by-doing. An idea in a similar vein provides exogenous variation in *Chapter 1*: Depending on how rugged the area is that you live in, the supply of infrastructure that enable new technologies may substantially differ.

But not all adoption of new technologies or ICT infrastructure is by chance. There can also be laggards on the side of the "lucky technology havers" while others are early adopters. This might be driven by various socio-demographic factors. *Chapter 3* shows that those who find their job online are different from those who found elsewhere, for example in terms of education. I consequently apply a matching method to make the two groups comparable and identify the effect of Online Job Finding on worker flexibility. In *Chapter 2*, I furthermore provide evidence that adoption of technology differs by age, as predicted by the psychological literature (e.g. Czaja et al., 2006). I also show in *Chapter 1* that the substitution of the incumbent technology with the new technology is weaker in areas where individuals are older.

All those analyses explore the respective research question empirically and rely on data that is rich and detailed. While it is on an individual level in *Chapters 2* and *3*, in *Chapter 1* we have information on the fine regional level of four digit postal code areas in Austria. Furthermore and importantly, all chapters contribute to the literature with some novel element. While *Chapter 1* proposes a new method to evaluate substitution relationships, *Chapter 2* is the first paper to causally identify the wage returns to measured digital skills. *Chapter 3* introduces a new measure of occupational distance, based on a machine learning algorithm comparing different job descriptions. A brief summary of every chapter is given in the following.

Chapter 1 investigates access substitution of fixed-line with mobile telephony in Austria, i.e. whether the steep upward slope of mobiles in Figure 0-1 pushed the downward slope of fixed-lines. Rules made a long time ago play an important role here as well. In many

European countries, the market for fixed-lines was a state monopoly and, even after the privatization that happened in the 1990s, prices stayed regulated and determined by a state authority. The question of substitution behavior between mobile and fixed-line technologies is a crucial issue in the context of regulation: In many countries and for a long time it was questioned whether mobile telephony is as big a game changer as to justify deregulation. We add to this issue by presenting evidence on the Austrian market where deregulation took place only in 2017 and use data from the period of 2011–2014, leading up to this development.

So far, the literature dealt with these problems by estimating cross-price elasticities. We propose a new method and estimate "cross-technological elasticities", depending on the availability and quality of mobile access, based on fine grained regional data at the postal code level. The underlying intuition is simple: The willingness of an individual to switch away from a given technology depends on the quality and availability of relevant alternatives in her region. This approach directly solves the measurement problem with respect to mobile prices: As long as mobile prices do not vary between and within postal code areas – the price schedules of providers are identical across Austria – they do not contribute to regional differences in switching behavior of households. We find that an increase in local mobile coverage has a sizable and significant effect on households' decisions to switch away from fixed-line contracts.

A central feature of the analysis is the utilization of technological availability of mobile technologies instead of actual usage because it accounts for potential biases resulting from unobserved characteristics of the local population. For example, the density of social networks is unobserved but may have an influence on telephone usage. Technological availability has been used as an instrument for utilization in previous studies, in particular Akerman, Gaarder, and Mogstad (2015), Bertschek, Cerquera, and Klein (2013) and Bhuller, Havnes, Leuven, and Mogstad (2013). However, to additionally overcome endogeneity concerns regarding the deployment of mobile infrastructure (e.g. operators rolling out mobile infrastructure in more profitable regions first), mobile availability is instrumented: We use the ruggedness of terrain within a given region which affects the roll-out costs of firms and hence availability.

Overall, we find that mobile coverage significantly, causally and sizeably affects the likelihood of customers switching away from fixed-line telephone contracts, i.e. that fixed-line and mobile access are substitutes in Austria. We furthermore present evidence on heterogeneous effects with respect to age. Results show that mobile coverage is perceived as a substitute to a smaller degree in regions with a high share of elderly population.

In *Chapter 2* we deal with information and communication technologies (ICT) as a game changer in the labor market. In particular, we look at the skills needed to master ICT as they are important complements to the technologies themselves. ICT has increasingly penetrated the business world and has consequently become an indispensable requirement of everyday life for large parts of the labor force. Hence, the skills to master these technologies are also referred to as “the new literacy”, for example by Neelie Kroes, the former Vice President of the European Commission, or “e-literacy”. We answer the question of how important mastering ICT really is in modern labor markets by presenting the first rigorous empirical evidence on the wage returns to (measured) ICT skills. We employ a unique dataset on ICT skills tested in 19 countries, called PIAAC (Programme for the International Assessment of Adult Competencies), administered by the OECD and also referred to as “PISA for Adults”.

The major empirical challenge is to assess whether any estimated association between ICT skills and wages indeed depicts a causal effect. A prime concern is that people with a higher general ability may be more likely to accumulate ICT skills and may receive higher earnings because of their higher ability anyway. Also, “better” or higher paying jobs may more likely use and reinforce skills or they may provide the resources to invest in adult education, training, or computer courses. These are only a few examples of the potential problems in a simple estimation of the wage returns to ICT skills. To address potential endogeneity concerns, we exploit technological peculiarities in the broadband Internet infrastructure because of which some individuals got access to high-speed Internet earlier than others simply by chance. We show that having (early) access to fast Internet kick-starts learning-by-doing in ICT skills.

In our first empirical strategy (cross-country strategy) we exploit the fact that existing fixed-line telephony networks were upgraded in most countries to provide broadband access. In consequence, the countries that had better-developed voice-telephony networks before the introduction of broadband in the late 1990s or early 2000s could roll out broadband faster than countries lagging behind in voice-telephony infrastructure. Our second empirical strategy (within-country strategy) makes use of the fact that some German municipalities are too far away from the necessary infrastructure to have had early access to broadband. This infrastructure was planned and rolled-out in the 1960s, when nobody expected new technologies to become a game changer - or even to exist at all. We observe that people who were lucky enough to have early broadband access (and be on the "winner side"), have higher ICT skills than their unlucky counterparts, but do not differ from them in their numeracy or literacy skills, which were also tested in PIAAC.

To address the potential concern in the cross-country strategy that richer and more productive countries have better-developed voice-telephony networks as well as higher wages and more skilled workers, we exploit that different age cohorts were differently affected by broadband and instrument ICT skills with an interaction between the extent of a country's initial voice-telephony network (determining the timing of introduction and diffusion of broadband) and age cohorts (determining the intensity of use of broadband). Doing so, we effectively identify returns to ICT skills based on differences in ICT skills and wages between age cohorts within countries.

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, i.e. the proliferation of personal computers causing a shift away from routine tasks – that is, those more amenable to automation – towards problem-solving and complex communication tasks (typically called nonroutine abstract tasks). 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. Indeed, we find that higher ICT skills increase the abstract task content of jobs and decrease their routine task content. Back-of-the-envelope calculations suggest that occupational selection explains a significant portion of the wage increase caused by higher ICT skills.

In *Chapter 3* I present results on how the Internet changes the way workers find jobs and in how far this changes worker flexibility. I use the German Socio-Economic Panel to look at the effect of Online Job Finding on occupational and regional change, i.e. whether Online Job Finding leads to individuals switching occupations/locations more (extensive margin) and also how much closer/more distant they move (intensive margin). While individuals do not switch occupations significantly more, they move to more *similar* occupations when switching. This provides a potential channel for the results in Mang (2016) that individuals are e.g. better able to use their skills on the new job when learning about it through an online job advertisement. Individuals changing to more similar occupations might simply be able to use more of their previously acquired task specific human capital. Additionally, I find individuals to move more and further away in geographic terms when they found out about their new job online.

Descriptive statistics of socio-demographics of Online Job Finders reveal them to be different from their Non-Online counterparts. Therefore, I use coarsened exact matching (Iacus, King, and Porro, 2009) to make the treatment and control group comparable. I also present robustness checks for whether the found effect is a pure information effect of the Internet or whether it comes from the possibility of Online Job Search.

The results suggest that Online Job Search indeed reduces frictions on the labor market by enabling more specific job search. Regarding the different directions of the geographic and occupational search, results could also be interpreted as workers being willing to switch geographically to stay in their occupational "comfort zone".

And now without further ado: Let the game (changers) begin.

Chapter 1

Regulating an industry undergoing technological change – The case of telecom in Austria[†]

1.1 Introduction

In a dynamic technological environment, when should regulators start taking alternative technologies into account as potential substitutes? In the case for or against regulation of an industry or in evaluating mergers, the market definition is an essential step – and more often than not it is the most hotly contested. Due to the importance of its infrastructure and the speed of technological development – consider the rapid rise of mobile and IP-telephony[1] – the telecom-sector has received considerable interest both from policy-makers and from academics. A central issue is to determine potential substitutes for fixed-line telephony. Typically, econometricians rely on (national level) cross-price elasticities to determine market boundaries.[2]

A series of studies using household-level survey data (see in particular Grzybowski and Verboven, 2016, Grzybowski, 2014, and Suárez and García-Mariñoso, 2013) show that the substitutive (or complementary) relationship between telephony technologies is complex and

[†]This chapter is joint work with Oliver Falck, Johannes Koenen and Andreas Mazat. We thank the A1 Telekom Austria AG for providing us with the data and Alexander Brosch and Peter Ptacek for sharing their knowledge on the Austrian fixed-line and mobile market.

[1]IP-telephony is also commonly referred to as "Voice over IP"

[2]For studies on the telecom-sector, see e.g. Barth and Heimeshoff, (2014a, 2014b), Briglauer, Schwarz, and Zulehner (2011), Garbacz and Thompson Jr (2007), Narayana (2008), Rodini, Ward, and Woroch (2003), Karacuka, Haucap, and Heimeshoff (2011), Ward and Woroch (2004), Ward and Woroch (2010), Ward and Zheng (2012). Also, see Lange and Saric (2016) for a recent overview of the literature.

may depend, for example, on socio-demographic characteristics of users.[3] In this paper, we focus on a different dimension which contributes to the complexity and which has not been systematically analyzed in the past: Heterogeneity in the availability of physical infrastructure and the competitive setting at the regional level. The market for telephony may and should behave very differently in a dense metropolis than in a sparsely populated rural area. Our analysis is informed by extremely fine-grained regional data from Austria at the postal code level. We make use of administrative contract information provided by the fixed-line incumbent, A1 Telekom Austria, for the time period 2011-2014 and study the extensive margin – whether a household has a fixed-line contract – instead of the intensive margin – how many minutes of telephony are carried out using fixed-lines vs. mobile phones (access substitution of fixed-lines). The data enable us to analyze the development of incumbent market penetration depending on regional characteristics in precise detail.

In the course of our analysis, we develop a new, alternative approach to assess the substitutability between different (telephony) technologies. The intuition underlying our approach is simple: The willingness of an individual to switch away from a given technology should depend on the quality and availability of relevant alternatives. Thus, we can exploit variation at the regional level to estimate "cross-technological" elasticities instead of classical cross-price elasticities. If the quality/availability of a given alternative positively affects switching behavior, then we have identified it as a substitute. By relying on the availability (instead of usage) of alternative infrastructure, we build on literature that quantifies the effect of broadband Internet on various economic and social outcomes (e.g. Akerman, Gaarder, and Mogstad, 2015; Bertschek, Cerquera, and Klein, 2013; Bhuller, Havnes, Leuven, and Mogstad, 2013).

The case of fixed-mobile substitution is a natural application for the approach of "cross-technological" elasticities: If mobile telephony is a substitute for fixed-lines, then a better quality of the mobile phone network in a given region should entice more customers to cancel their fixed-line subscriptions, all else given. In this context, we are also able to address causality. Regional variation in the availability of alternative technologies may in itself be endogenous. The roll-out of mobile telephony infrastructure is driven by operators' profit considerations and therefore most likely related to the characteristics of the respective regions; there may be a stronger focus on regions with more (or more affluent) potential customers, for example. To address this endogeneity issue and identify causal effects, we

[3] In a similar vein, Vogelsang (2010) argues that simply estimating elasticities may not sufficiently take supply side effects into account.

apply an instrumental variable strategy exploiting geographical peculiarities in the Austrian surface contour that cause exogenous variation in mobile coverage: The ruggedness of terrain within a given area (Riley, DeGloria, and Elliot, 1999). This type of instrument has previously been used in the economic literature (e.g. Kolko, 2012; Klonner and Nolen, 2010).

The application of the Terrain Ruggedness Index to Austria seems very natural, as large parts of the country are covered by the alps, the largest mountain chain in inner Europe, stretching from France in the West over Switzerland, Italy and Germany and finally Austria in the East. The areas more in the East of the country, e.g. around the capital of Vienna, are less rugged, but still show some variation. To not compare individuals in very rugged with individuals in less rugged parts, we include region fixed effects at the level of two-digit postal code areas. Furthermore, we include a whole set of geographic and socio-economic covariates. This identification strategy solves the endogeneity problem regarding, for example, omitted variables, such as unobserved market factors, which might drive mobile coverage and numbers of fixed-lines alike.

Importantly, for the exclusion restriction to be valid, in Austria we can exclude any direct effect of the TRI on fixed-lines. In many countries, telecommunications were a state monopoly up and running until the 1990s. Those often had a universal service obligation, i.e. providing every household with fixed-line access. As Austria was one of them (see e.g. OECD, 2010, p. 135) even the most remote household should have access, no matter the ruggedness. According to data from the International Telecommunications Union (ITU), in the mid 90s (1996), before mobile really took off, there were even more fixed-lines in operation than households in Austria, at a rate of 1.24.

Our approach is complementary to the existing literature on fixed-mobile substitution. At the center of our analysis is the heterogeneity of (postal code) regions with regard to the availability of alternative technologies. This factor is typically not incorporated in cross country- or country level analyses (such as Grzybowski, 2014; Briglauer, Schwarz, and Zulehner, 2011; Garbacz and Thompson Jr, 2007; Gruber and Verboven, 2001; Lange and Saric, 2016; Barth and Heimeshoff, 2014a, 2014b), which mostly find a substitutive relationship between the two technologies. Even studies using rich household survey data such as Grzybowski and Verboven (2016), who show that the substitution pattern has become stronger in the more recent past, lack detailed information at the regional level and can therefore not take this underlying mechanism into account.

Furthermore, our estimation approach addresses an important issue regarding the estimation of cross-price elasticities in the context of mobile-telephony (and, more generally, many innovative products). Non-linear price schedules – such as combination of base price, included volume of minutes plus a per minute price if that volume is exceeded – make assumptions regarding (the distribution of) usage profiles in the population necessary. Especially in the mobile market, we observe a high degree of (strategic) price differentiation, making price comparisons difficult not only for consumers, but also for the researchers trying to assess the effective prices in their estimation approach. Therefore, reducing "mobile price" at a given point in time to a singleton is not necessarily appropriate. Our estimation approach directly solves the measurement problem with respect to prices: As long as mobile prices do not vary regionally – the price schedules of providers are valid across Austria – they do not contribute to regional differences in switching behavior of households, which is the source of our identification strategy.

This underlying mechanism driving our results is of immediate importance for regulators – the existence of regional variation in the availability and quality of alternative technologies implies that the incumbent's market power differs regionally in ways that are objectively measurable. Regulatory decisions in telecommunications are, at least in part, driven by worries concerning access and availability at the regional level. Therefore, an optimal regulatory regime should take this variation into account. *Local* telecom (de-)regulation has, to the best of our knowledge, so far only been considered with regard to broadband access markets in certain European countries (see Fabritz and Falck, 2013).

The rest of this paper is organized as follows. Section 1.2 gives a brief overview of the institutional setting in the Austrian telecom market. Section 1.3 describes the data. Section 1.4 presents our empirical model and identification strategy. Section 1.5 includes our main empirical findings, as well as robustness and heterogeneity analyses. Section 1.6 concludes.

1.2 The Market for Telephony

The market for fixed-lines in Austria, as well as in many other countries, was a state monopoly with a universal service obligation. In Austria all telecommunications had been under governmental authority as part of the "Post- und Telegrafenverwaltung (PTV)" since 1887. This construct was only dissolved in 1996, when the "Post- und Telekom Austria AG (PTA AG)" was founded in course of the privatization of telecommunication services. In 2010, the incumbent got the name still valid until today: A1 Telekom Austria AG.[4] However, even then, almost 15 years after privatization, prices for fixed-line telephony remained regulated and determined by the Austrian regulation authority (Telekom-Control-Kommission).

Only in 2017 the authority decided that the substitutive relationship between mobile and fixed-lines was sufficiently large to count market shares of mobile operators into the market for fixed-line access (Telekom-Control-Kommission, 2017). What followed, was the deregulation of the incumbent who, under the new regime, did not have a worrisome share of market power anymore. In our analysis, we use data from the phase 2011 to 2014, leading up to this decision.

1.3 Data

For our analysis, we use highly dis-aggregated regional data for 2,216 4-digit postal code areas across Austria. On average, these postal code areas stretch over an area of 37 square kilometers. While data on fixed-line usage, mobile network and infrastructure (e.g. road and railway) coverage is available on postal code level, regional socio-economic characteristics are provided on municipality level. Converting municipality level data to postal code level is complicated by the fact that they are not nested within each other. Therefore we use geographic information software to generate area weights which are then used to re-code our data in ArcGIS.[5]

1.3.1 Fixed-line Usage & Mobile Coverage

Postal code level information on the number of fixed-line contracts of A1 Telekom Austria are drawn from the firm's administrative database. We observe the number of active contracts in a particular month in 2011 and 2014, which we average up to the yearly level.[6] We use this data to calculate A1 fixed-line market penetration. It is measured as the number

[4] `https://www.a1.group/en/group/history`; last accessed February 27, 2018.

[5] In detail, we calculate the share of a municipality's total building ground area that is located in a particular postal code area. We use this to assign e.g. the absolute number of people at a specific age or with a specific education of a municipality to a postal code area by multiplying the number of a these people within a specific municipality with the building ground share. This procedure assumes that overall population as well as population characteristics are distributed uniformly across building ground areas of municipalities.

[6] We drop postal code areas with missing information on the number of active fixed-line contracts in more than 6 months of either 2011 or 2014. This reduces the number of observations from 2,216 to 2,215.

of A1 Telekom Austria fixed-line contracts, providing voice telephony services, as a fraction of households within a postal code area. On top of voice telephony services, these contracts may also include broadband Internet and television services. The upper Panel in Table 1-1 illustrates that the average A1 fixed-line market penetration across all postal code areas in our sample dropped by 8 percentage points between 2011 and 2014, from 58 percent to 50 percent. This corresponds to an average growth rate, approximated as difference in natural logarithms of market penetration between 2011 and 2014, of –15 percent. 98.98 percent of all postal code areas in our sample exhibit a negative growth rate between 2011-2014. In the following, we therefore refer to the percentage change in A1 Telekom Austria fixed-line voice telephony penetration between 2011 and 2014 as fixed-line penetration decline rate.

Our main explanatory variable of interest is mobile network quality. We derive mobile network quality in postal code areas across Austria from two different sources. First, A1 Telekom Austria's market intelligence unit provides postal code level information on 2G and 3G mobile outdoor coverage in 2015. The middle Panel in Table 1-1 depicts that nearly all postal code areas are fully covered by 2G networks while 3G coverage amounts to 80 percent on average. With a factor close to five, regional variation in 3G coverage is substantially larger than variation in 2G coverage across Austrian postal code areas. Variation in our first measure of mobile coverage, which is the average of 2G and 3G mobile coverage, thus mainly arises from regional differences in the coverage of 3G networks. Overall, Table 1-1 illustrates that average mobile coverage of all Austrian postal code areas is 89 percent. Our second measure of coverage is derived from data of the Austrian broadband atlas which is provided by the Ministry for Transport, Innovation and Technology. It provides information on local mobile coverage by bandwidth for more recent years. We use data for 2016 to calculate the share of a postal codes's area covered by mobile networks, technically allowing for bandwidths of 10 Mbit/s or more.[7] Table 1-1 shows that about 84 percent of the average postal code area is covered by mobile networks, providing such a bandwidth. Apart from mobile coverage, we also derive the number of fixed-line operators active within a particular postal code area from the broadband atlas. We use this information to construct three dummy variables that are equal to unity if 0, 1-3 or ≥ 4 fixed-line operators other than A1 Telekom Austria are active in the postal code area and zero otherwise. Table 1-1 (bottom) illustrates that in the majority of postal code areas 1-3 alternative fixed-line providers are active.

[7]Actual bandwidth reached depends importantly on exact location of the mobile user and the number of people that are connected to the same node.

Table 1-1: Descriptive Statistics

	Mean	SD	Min	Max
Fixed Line Usage				
FL p.hh. 2011	0.58	0.52	0.03	20.08
FL p.hh. 2014	0.50	0.52	0.02	20.31
Δ FL p.hh. (2014-2011)	-0.08	0.04	-0.74	0.23
Log of FL p.hh. 2011	-0.63	0.34	-3.49	3.00
Log of FL p.hh 2014	-0.79	0.38	-4.03	3.01
A1 FL p.hh. rate of change (2011-2014)	-0.15	0.07	-0.54	0.03
Technological Variables				
2G Coverage	0.99	0.06	0.00	1.00
3G Coverage	0.80	0.29	0.00	1.00
Mobile Coverage	0.89	0.16	0.00	1.00
Mobile $\geq$10Mbit/s	0.84	0.21	0.01	1.00
Demographic Controls				
HH Density 2011	0.10	0.65	0.00	13.62
Dist. City $\geq$100k (in km)	56.28	30.78	0.24	146.35
Dist. Highway (in km)	13.82	13.29	0.01	75.66
Dist. Railway (in km)	5.38	5.68	0.00	41.07
Fraction Female 2011	0.50	0.01	0.41	0.65
Fraction Unemployed 2011	0.05	0.03	0.00	0.34
Fraction Foreigners 2011	0.08	0.06	0.01	0.69
Fraction Secondary Educ. 2011	0.63	0.04	0.43	0.74
Fraction Tertiary Educ. 2011	0.08	0.04	0.00	0.39
Fraction >65 2011	0.18	0.03	0.09	0.40
Fraction Students 2011	0.04	0.01	0.01	0.10

	0	1-3	$\geq$4
No. alternative operators (%)	1.84	63.56	21.48

Notes: Table shows 4-digit postal code area averages. Data sources: A1 Telekom Austria, Statistik Austria, Broadband Office of the Austrian Ministry for Transport, Innovation and Technology and GfK GeoMarketing GmbH.

1.3.2 Geographic and Demographic Data

We obtain data on population and household numbers on postal code level, as well as demographic characteristics such as age, education and employment, among others from Statistik Austria. Furthermore, we gather information from GfK Geomarketing GmbH on geographic attributes, which we use to calculate measures of transport infrastructure availability, namely the distance to the closest highway and the closest railway.

We have full information on all relevant variables for 2100 out of 2216 postal code areas. To avoid outliers affecting our analysis, we drop the top and bottom percentile of postal code areas with regards to the log difference of A1 fixed-line market penetration between 2011 and 2014. Consequently, our final data set contains 2,058 postal code areas covering 90 percent of all Austrian households in 2014.

1.4 Empirical Model

1.4.1 Underlying Mechanism and the Nature of the Involved Products

Our empirical strategy is driven by the fact that we observe the decision of consumers to *switch away* from fixed-line telephone contracts, depending on the availability of alternative technologies. This requires that the alternative technology is actually a substitute (from the perspective of consumers). The classic approach considers cross-price elasticities. In our case, though, this is fraught with substantial difficulties: First of all, there is a plethora of available price offerings for mobile telephony contracts, which makes it almost impossible to determine (a set of) relevant mobile prices at any given time. Secondly, this approach has to rely solely on price-variation over time, since there are no cross-sectional regional price differences in the Austrian market. Our identification strategy addresses both of these issues while making efficient use of the structure of our unique dataset including detailed regional information.

To briefly motivate our modelling choices, consider the decision of a budget-restrained decision maker choosing a telephony product. Fixed-line telephony (FL) is a mature technology with constant quality and availability. The network of A1 Telekom Austria reaches every household in Austria. The quality of the alternative technology (AT), mobile, on the other hand, may vary substantially. Define $u_{\mathrm{j}}(k)$ as the utility that consumer j derives from using a given technology k for a time-period in monetary terms and p_{k} as technology k's per period cost to the consumer. If the decision maker picks either one or the other (i.e., if they were perfect substitutes), for any given prices there is a critical quality level of the alternative technology q^*_{AT} such that the decision maker is exactly indifferent between FL and AT, as $u_{\mathrm{j}}(FL) - p_{\mathrm{FL}} = u_{\mathrm{j}}(AT, q^*_{\mathrm{AT}}) - p_{\mathrm{AT}}$, assuming that the utility of the decision maker is increasing in the quality of AT. Therefore, similarly to the cross-price elasticity between the two technologies, which is based on the fact that individuals will switch from one technology to the other as the relative prices change, if the technologies are substitutes, we should find a cross-technological elasticity between technologies; i.e., as the quality of mobile (AT) increases, the likelihood of choosing FL decreases.[8]

As a measure for AT, we use the average mobile coverage of 2G and 3G. 2G, while perfectly sufficient for pure voice telephony, does not provide sufficient bandwidth for most web-services (or even dedicated mobile apps). 3G can be seen as a substitute with regard to voice telephony, but also provides additional features, such as Internet capabilities, over which communication is possible as well. This provides us with another rationale to include both standards in our indicator for mobile availability, as they are both important in different dimensions. However, importantly for our identification, both technologies are affected by the ruggedness of the terrain when in comes to the roll-out costs.

While prices do not vary regionally, we would still like to control for socio-demographics that might be associated with budget constrainedness. Individuals in "richer" regions might be more inclined to have both, fixed and mobile access, where a more budget constrained individual has to decide for one of the two technologies.

1.4.2 OLS Approach

We empirically estimate cross-technological elasticities. This approach allows us to make use of the fact that there is substantial heterogeneity with regard to the availability and quality of mobile coverage among the more than 2,000 Austrian postal code areas in our sample. In principle the relationship is the following:

$$FL_{\mathrm{i}} = \alpha + \beta_1 MobileCoverage_{\mathrm{i}} + \boldsymbol{X}_{\mathrm{i}}\boldsymbol{\beta_2} + \varepsilon_{\mathrm{i}} \tag{1.1}$$

Here, FL is the share of decision makers using fixed-line technology in postal code area i. $MobileCoverage$ represents the availability of mobile telephony. The vector X is composed of variables that capture the economic structure and geographic remoteness of the postal code area, including unemployment rate, population density, age structure, distance to the

[8] This wider understanding of substitution relationships is, e.g., in line with Vogelsang (2010).

next bigger city, etc. ε is the stochastic error term. Clearly, mobile and fixed-lines are substitutes if β_1 is negative.

Macro-level developments in the market for telecommunication further inform our estimation strategy. Fixed-line telephones are the incumbent technology, whose overall market penetration is in decline. We are typically not observing the original purchase decision of consumers. Instead, within a changing technological environment, individuals (periodically) re-evaluate their telecommunication contracts. Intuitively, we are not looking at a market in equilibrium, but at a shift from one equilibrium, in which the incumbent fixed-line technology was the overwhelming standard, to a new equilibrium with more technological diversity. Accordingly, to capture the substitution relationship between technologies, we have to focus on the switching behavior of decision makers. We estimate the following empirical model:[9]

$$\begin{aligned}\Delta(\ln FL_{\mathrm{it=1}}, \ln FL_{\mathrm{it=0}}) =&\alpha_L + \beta_1 \ln FL_{\mathrm{it=0}} + \beta_2 MobileCoverage_{\mathrm{it=0}} + \\ &\beta_3 INF_{\mathrm{it=0}} + \boldsymbol{X}_{\mathrm{it=0}} \boldsymbol{\beta_4} + \varepsilon_{\mathrm{it}}\end{aligned} \tag{1.2}$$

The dependent variable is the A1 fixed-line decline rate, i.e. the difference in natural logarithms of A1 fixed-line voice telephony market penetration in postal code area i between $t = 0$ (2011) and $t = 1$ (2014). By including two digit postal code fixed effects (α_{L}) we compare only postal code areas within the same region, e.g. postal code areas within a certain area of Vienna, to account for regional differences in population and geographic characteristics that exceed the explicit controls. $X_{\mathrm{it=0}}$ is a vector of such socio-economic characteristics of the postal code area including, e.g., age and education structure as well as the unemployment rate for 2011, among others.

We control for the initial share of fixed-line subscribers in 2011 in the postal code area ($\log FL_{\mathrm{it=0}}$) to account for the fact that switching behavior of consumers in a given time period likely not only depends on the current availability of alternative technologies, but also on previous developments. If, for example, the mobile technology was introduced earlier in area A, but only recently in area B, then the pool of potential switchers and the probability of any given individual to switch, could be higher in area B than in A, where many poten-

[9]The functional form is equivalent to a cross-country growth regression, see e.g. Barro (1991).

tial switchers may have switched already.[10] We use robust standard errors throughout all regressions.

This specification also directly takes potential issues with regard to the heterogeneity of developments across regions into account. If certain (e.g., detached rural) regions remain captive to fixed-line technology, perhaps because of a lack of alternatives or due to the educational composition of inhabitants, then the coefficient β_1 should be positive; alternatively, if there is a tendency towards a homogenous outcome (i.e., regions are becoming more similar), then the coefficient should be negative, as regions in which more consumers originally remained experience a larger A1 fixed-line decline rate.

In all our specifications, we control for the distance of a postal code's geographic center to the closest railway and highway, included in $INF_{\text{it}=0}$. This is important since proximity of transport infrastructure not only affects mobile coverage through network deployment costs or the operators' objective to provide mobile services to their traveling customers. It also correlates with regional differences in the economic capacity and socio-demographic composition of the local population. In order not to confound an increased mobile coverage with such differences in the economic and demographic surrounding, controlling for differences in the proximity of transport infrastructure is important.

$INF_{\text{it}=0}$ also includes a set of dummy variables that are equal to one, if there are 1-3 or 4 and more fixed-line network providers[11] active in a certain postal code area. This should account for the fact that A1 fixed-line customers may not only give up their fixed-line contracts to switch to mobile only usage. They may also switch to other fixed-line network providers instead. Given that roll-out costs of alternative fixed-line infrastructure may be correlated with the cost of mobile infrastructure deployment, a higher degree of mobile coverage may come along with a higher degree of competition in the market for fixed-line voice telephony. As a consequence, parts of the effect of mobile coverage on the A1 fixed-line decline rate may be actually due to higher local competition rather than a true mobile coverage effect.

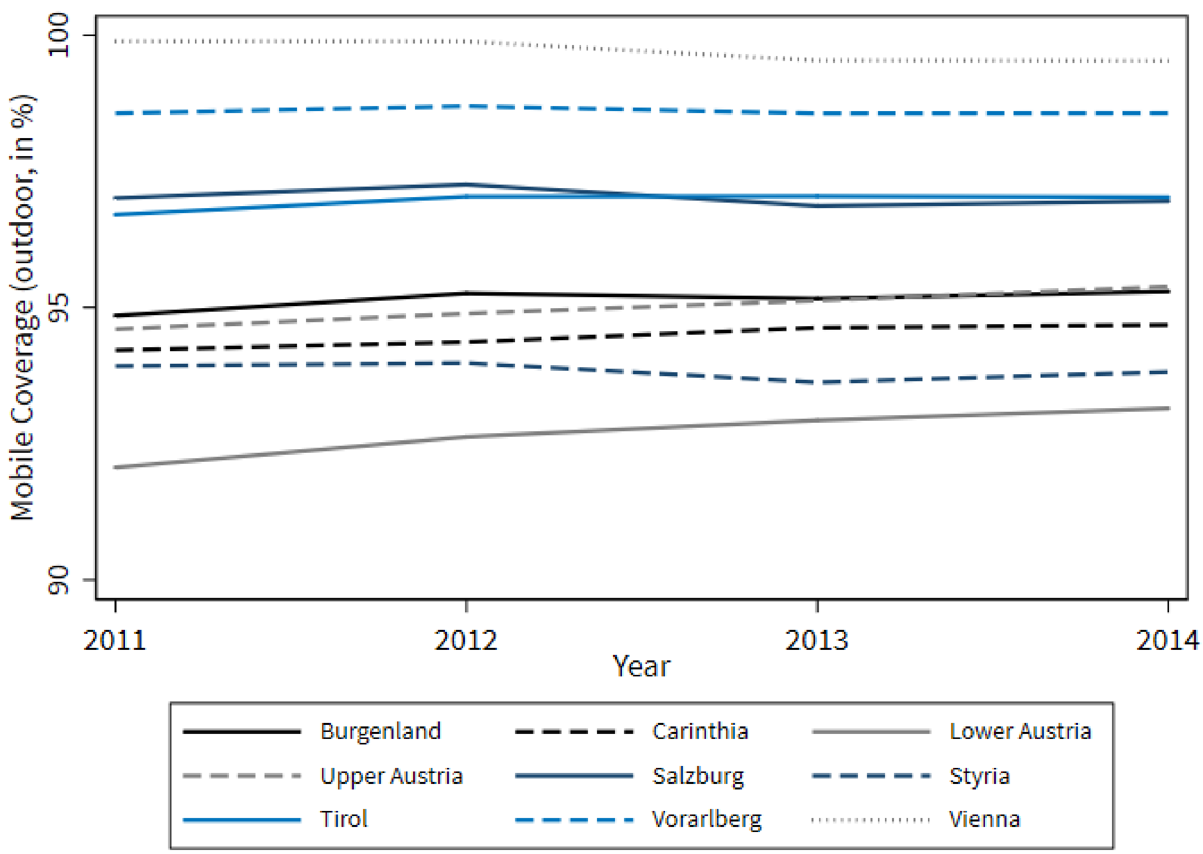
Our main coefficient of interest is the estimate on mobile coverage, β_2. It measures the relationship between increased mobile coverage and fixed-line telephony usage. In particular, β_2 indicates how strongly increased mobile coverage affects the rate of change in the number

[10] Also in models for demand analysis, e.g. the Houthakker-Taylor model (Houthakker and Taylor, 1970), possible path dependencies of consumption are taken into account. These are usually represented in the demand equation by lagged dependent variables.

[11] We only include network providers with own infrastructure. Unbundling operators are not included.

of A1 fixed-line accesses between 2011 and 2014. Unfortunately, we observe mobile coverage, for which we use the unweighted mean in 2G and 3G availability, on postal code level only in 2015 rather than 2011. However, Figure 1-1 illustrates for each of the nine Austrian states that mobile coverage has been very stable. Therefore, we use mobile coverage in 2015 as a proxy for mobile coverage in 2011.

Figure 1-1: Development of Mobile Coverage across Austrian States



Notes: Figure depicts the average of 2G and 3G mobile outdoor coverage across Austrian states between 2011 and 2014. *Data source:* A1 Telekom Austria.

A central feature of our analysis is the utilization of availability of mobile technologies instead of actual usage. This counters potential biases resulting from unobserved characteristics of the local population that affect adoption but not (or to a lesser extent) the roll-out of mobile infrastructure. For example, unobserved density of social networks may have an influence on telephone usage. At the same time, customers with higher-usage may be more likely to use both fixed-line and mobile telephony. Using availability rather than usage exploits the fact that single individuals are typically unable to influence technological availability in their area. Technological availability has been used as an instrument for utilization in previous studies, in particular Akerman, Gaarder, and Mogstad (2015), Bertschek, Cerquera, and Klein (2013) and Bhuller, Havnes, Leuven, and Mogstad (2013).

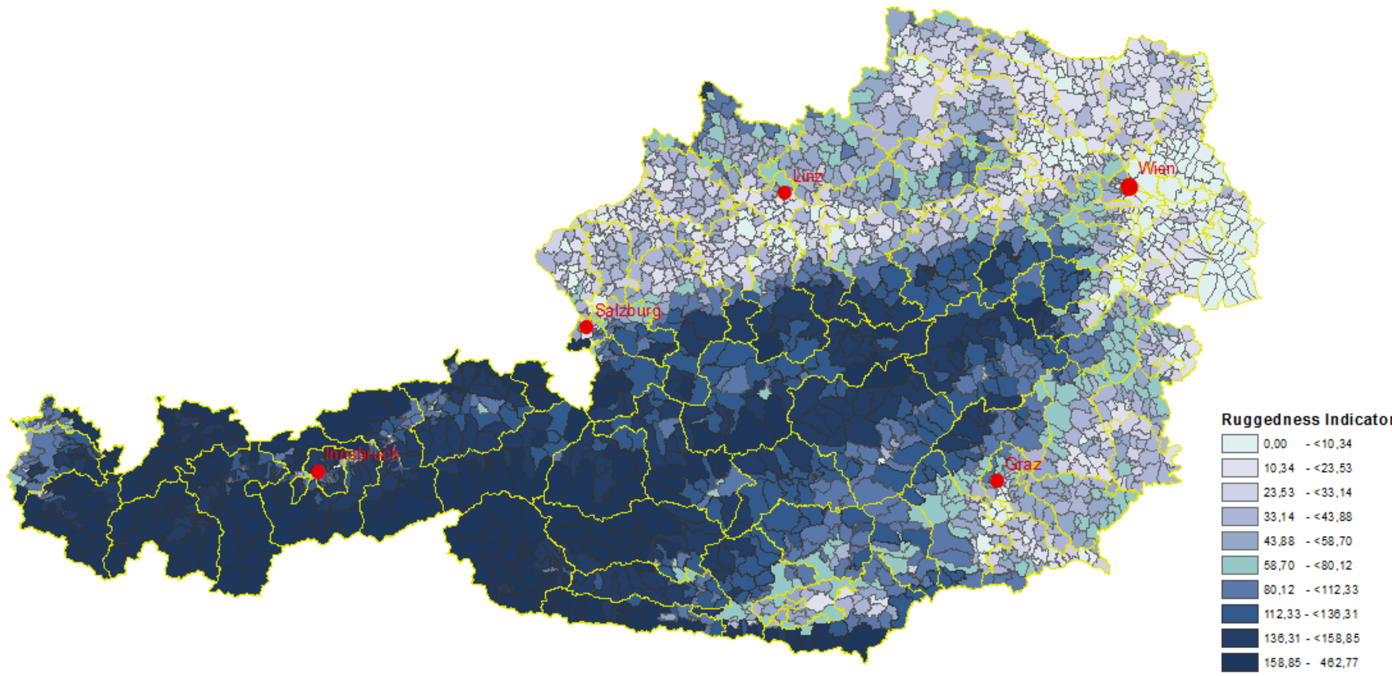
1.4.3 Identification

Even though we use availability rather than actual usage, a remaining potential source of endogeneity is the fact that network providers do not carry out infrastructure investments randomly. We would expect them to be more likely to improve the quality of their networks in those areas where they expect higher overall telephony demand. The direction of the bias depends on the underlying strategic motives: If investment focuses on wealthier regions, where customers are more likely to have a fixed-line contract and a mobile subscription, this would bias our results toward underestimating the substitutive relationship. If, on the other hand, the focus of investments was to cut into the incumbent fixed-line market share, we would over-estimate the effect.

As pointed out before, we rely on data from market intelligence for the main independent variable, mobile coverage, likely prone to some degree of measurement error, leading to a bias of the OLS coefficient towards zero. Also market factors, driving mobile coverage and numbers of fixed-lines alike might be unobserved, leading to omitted variable bias. We counter these problems by making use of an instrumental variable approach. The underlying idea is that mobile infrastructure roll-out is more expensive in regions with rugged terrain. This should particularly apply to the (also more recent) roll-out of 3G-technology: While 2G mobile radio signals spread to a wide circle of up to 35 km radius,[12] 3G technologies cover only a much smaller radius. Consequently, comprehensive 3G mobile coverage of the population requires substantial infrastructure investments, in addition to the already existing 2G-network. The idea of ruggedness as an instrument has been previously used in the economic literature (e.g. Kolko, 2012; Klonner and Nolen, 2010).

[12]`https://www.4g.de/service/lexikon/2g/`; in German, last accessed January 7, 2018.

Figure 1-2: Ruggedness across Austria



Notes: Figure illustrates the ruggedness of Austrian 4-digit postal code areas. The darker the area, the more rugged a postal code area is. Ruggedness index is defined according to Riley, DeGloria, and Elliot (1999). Yellow lines represent 2-digit postal code areas. *Data sources:* GfK Geomarketing GmbH.

We measure ruggedness according to the terrain ruggedness index (TRI) as proposed by Riley, DeGloria, and Elliot (1999). Figure 1-2 depicts the average terrain ruggedness indicator for all postal code areas across Austria. Therein, dark shaded areas represent highly rugged postal code areas while lighter shaded areas are comparatively smooth. Importantly, identification relies on the fact that we compare only postal code areas within the same region (two digit postal code area, depicted by yellow lines in Figure 1-2) with each other, while at the same time controlling for our set of demographic and infrastructure characteristics (that may be related to ruggedness). Instrumenting $MobileCoverage$ with the TRI yields the following first stage equation:

$$MobileCoverage_{\mathrm{it=0}} = \rho_L + \gamma_1 \ln FL_{\mathrm{it=0}} + \gamma_2 TRI_{\mathrm{i}} + \gamma_3 INF_{\mathrm{it=0}} + \boldsymbol{X}_{\mathrm{it=0}}\boldsymbol{\gamma_4} + \epsilon_{\mathrm{it}} \tag{1.3}$$

TRI stands for the terrain ruggedness index. Because of a universal service obligation of the fixed-line incumbent, we can rule out any direct effects of the TRI on fixed-lines, leaving the exclusion restriction unharmed. Regarding $MobileCoverage$ we use the values of 2015, as a proxy for 2011 throughout. However, as Figure 1-1 showed, there were hardly any changes in mobile coverage. The underlying idea behind this strategy is, that ruggedness affects roll-out costs, affecting roll-out, affecting the level of availability in 2011. Mobile availability in 2011 then in turn enables switching from fixed-lines between 2011 and 2014.

1.5 Results

1.5.1 Substitution Behavior

In this section, we present the results of our estimations. Table 1-2 displays the findings from the OLS specification. To account for path dependencies in switching behavior, we control for initial fixed-line diffusion in all specifications. Besides, all specifications include measures for the proximity of transport infrastructure. In Column (2)-(5), we further control for local competition in the fixed-line voice telephony market. Starting in Column (3), we progressively add socio-economic and demographic control variables. Besides, we include two-digit postal code fixed effects in all specifications. Thus, we only compare postal code areas in similar regions with each other, e.g. different postal code areas in the greater area of Vienna. The estimate in our preferred specification in Column (5) indicates that an increase in mobile coverage by 10 percentage points increases the A1 fixed-line decline rate by 0.55

Table 1-2: Results from Ordinary Least Squares Regressions

Dependent Variable: A1 FL p.hh. rate of change (2011-2014)					
	(1)	(2)	(3)	(4)	(5)
Mobile Coverage	-0.0666***	-0.0653***	-0.0679***	-0.0552***	-0.0550***
	(0.0105)	(0.0106)	(0.0106)	(0.0107)	(0.0107)
Log of FL p.hh. 2011	0.0407***	0.0396***	0.0405***	0.0352***	0.0355***
	(0.00630)	(0.00629)	(0.00637)	(0.00640)	(0.00640)
Dist. Highway (in km)	0.000855***	0.000782***	0.000942***	0.000952***	0.000952***
	(0.000182)	(0.000186)	(0.000189)	(0.000189)	(0.000195)
Dist. Railway (in km)	0.00228***	0.00218***	0.00209***	0.00194***	0.00192***
	(0.000300)	(0.000303)	(0.000308)	(0.000314)	(0.000314)
$1-3$ alternative FL operator		-0.00524	-0.00484	-0.00481	-0.00482
		(0.00434)	(0.00430)	(0.00434)	(0.00434)
≥ 4 alternative FL operator		-0.0146**	-0.0144**	-0.00998	-0.0104*
		(0.00610)	(0.00609)	(0.00610)	(0.00617)
Fraction Students 2011			0.0139	0.0837	0.0456
			(0.159)	(0.161)	(0.187)
Fraction >65 2011			-0.193***	-0.101*	-0.121**
			(0.0540)	(0.0580)	(0.0594)
Fraction Female 2011				-0.333***	-0.336***
				(0.122)	(0.122)
Fraction Foreigners 2011				-0.160***	-0.165***
				(0.0400)	(0.0429)
Fraction Unemployed 2011				-0.00700	-0.00622
				(0.0707)	(0.0721)
Fraction Secondary Educ. 2011					-0.0532
					(0.0496)
Fraction Tertiary Educ. 2011					0.0156
					(0.0574)
Two Digit FE	X	X	X	X	X
N	2058	2058	2058	2058	2058

Notes: Mobile Coverage represents the average fraction of households that is covered by 2G and 3G networks. Heteroscedasticity robust standard errors in parentheses. Significance levels: * p<0.10, ** p<0.05, *** p<0.01. *Data sources:* A1 Telekom Austria, Statistik Austria and GfK GeoMarketing GmbH.

percentage points. Moreover, our results indicate that fixed-line usage is becoming less similar across regions over time: The coefficient with regard to the market penetration in 2011 has a positive sign throughout our specifications, indicating that A1 Telekom Austria fixed-line customers tend to switch away less in postal code areas where A1 market penetration is relatively high. Our other basic control variables enter with the expected sign. Our estimate on the proximity of transport infrastructure, for example, has a positive sign and is statistically significantly different from zero. Higher competition in turn increases the speed of decline of A1 fixed-line penetration between 2011 and 2014.

We provide the corresponding IV estimates in Table 1-3. Regarding the inclusion of controls, we proceed analogously to Table 1-2. Our first stage coefficients indicate that the more rugged a certain postal code area is, the lower is mobile coverage. As indicated by the Kleibergen-Paap F-statistics, our excluded instrument explains a substantial amount of the variation in mobile coverage across postal code areas.

In the most inclusive specification in Column (5), we observe that an increase in mobile coverage by 10 percentage points increases the A1 fixed-line market penetration decline rate by 2.85 percentage points. Pushing the average mobile coverage (90 percent) postal code area to full mobile coverage, would thus accelerate A1 fixed-line market penetration decline by about 19 percent, from the, on average observed, –15 percent to –17.85 percent between 2011 and 2014.

The coefficients from the instrumental variable estimations are significantly larger in absolute terms compared to coefficients of our OLS regressions. However, measurement error in our explanatory variable of interest, mobile coverage, may lead to attenuated OLS coefficients. In Table 1-4, we provide evidence, that part of the difference between OLS and IV coefficients indeed stems from the fact that mobile coverage is measured with error. In detail, we exploit information on mobile network coverage from the Austrian broadband atlas to instrument our preferred measure of mobile coverage, provided by A1 Telekom Austria. Given that the data from the broadband atlas is measured without error or, at least, an error that is independent from the one in our basic measure, this should remove attenuation bias. The corresponding results are provided in Column (3) of Table 1-4, while Columns (1) and (2) show the baseline OLS and IV coefficient, respectively. This illustrates that approximately 60 percent of the difference between our OLS and IV coefficient likely stem from measurement error.

Table 1-3: Results from Instrumental Variable Regressions

Dependent Variable: A1 FL p.hh. rate of change (2011-2014)					
	(1)	(2)	(3)	(4)	(5)
Mobile Coverage	-0.198**	-0.185**	-0.254**	-0.277***	-0.285***
	(0.0829)	(0.0852)	(0.100)	(0.100)	(0.100)
Log of FL p.hh. 2011	0.0311***	0.0312***	0.0278***	0.0250***	0.0246***
	(0.00937)	(0.00930)	(0.0102)	(0.00902)	(0.00904)
Dist. Highway (in km)	0.000547**	0.000528**	0.000613**	0.000571**	0.000649**
	(0.000260)	(0.000254)	(0.000259)	(0.000261)	(0.000252)
Dist. Railway (in km)	0.00139**	0.00142**	0.000913	0.000664	0.000612
	(0.000664)	(0.000651)	(0.000746)	(0.000706)	(0.000702)
$1-3$ alternative FL operator		-0.00126	0.00122	0.00160	0.000679
		(0.00522)	(0.00568)	(0.00560)	(0.00543)
≥ 4 alternative FL operator		-0.00951	-0.00721	-0.00485	-0.00701
		(0.00693)	(0.00727)	(0.00686)	(0.00686)
Fraction Students 2011			0.157	0.146	-0.0715
			(0.190)	(0.186)	(0.226)
Fraction >65 2011			-0.255***	-0.266**	-0.299***
			(0.0723)	(0.104)	(0.107)
Fraction Female 2011				0.105	0.0831
				(0.235)	(0.224)
Fraction Foreigners 2011				-0.120**	-0.142***
				(0.0470)	(0.0474)
Fraction Unemployed 2011				0.134	0.163
				(0.103)	(0.109)
Fraction Secondary Educ. 2011					-0.0138
					(0.0580)
Fraction Tertiary Educ. 2011					0.139*
					(0.0776)
First stage (Dependent Variable: Mobile Coverage)					
TRI	-0.618***	-0.597***	-0.554***	-0.554***	-0.576***
	(0.16)	(0.159)	(0.16)	(0.16)	(0.146)
Kleibergen-Paap F-statistic	31.11	29.49	24.51	29.67	30.17
Two Digit FE	X	X	X	X	X
N	2058	2058	2058	2058	2058

Notes: Mobile Coverage represents the average fraction of households that is covered by 2G and 3G networks. Heteroscedasticity robust standard errors in parentheses. Significance levels: * p<0.10, ** p<0.05, *** p<0.01. *Data sources:* A1 Telekom Austria, Statistik Austria and GfK GeoMarketing GmbH.

Table 1-4: Measurement Error

Dependent Variable: A1 FL p.hh. rate of change (2011-2014)			
	OLS	IV	IV
		TRI	Mobile ≥10Mbit/s
Mobile Coverage	-0.0550***	-0.285***	-0.148**
	(0.0107)	(0.100)	(0.0641)
First stage (Dependent Variable: Mobile Coverage)			
First Stage Coefficient		-0.576***	0.165***
		(0.146)	(0.032)
Kleibergen-Paap F-statistic		30.17	46.51
Two Digit FE	X	X	X
N	2058	2058	2058

Notes: Mobile Coverage represents the average fraction of households that is covered by 2G and 3G networks. Heteroscedasticity robust standard errors in parentheses. Significance levels: * p<0.10, ** p<0.05, *** p<0.01. *Data sources:* A1 Telekom Austria, Statistik Austria and GfK GeoMarketing GmbH.

1.5.2 Effect Heterogeneity

Typically, regulators are not only interested in the well-being of the *average* region or consumer. The existence of need-based tariff reductions across Europe is an indication for this.[13] Therefore, the substitution behavior of (from an ex-ante perspective) particularly vulnerable groups are of considerable importance. One example are elderly people that are typically perceived as less flexible with regards to changing contracts and adoption of new technologies. To investigate this empirically, we estimate the following model:

$$\begin{aligned}\Delta(\ln FL_{\text{it=1}}, \ln FL_{\text{it=0}}) =& \alpha_L + \beta_1 \ln FL_{\text{it=0}} + \beta_2 MobileCoverage_{\text{it=0}} + \\ & \beta_3 MobileCoverage_{\text{it=0}} \times shareX_{\text{it=0}} + \beta_4 shareX_{\text{it=0}} + \\ & \beta_5 INF_{\text{it=0}} + X_{\text{it=0}}\beta_6 + \varepsilon_{\text{it}}\end{aligned} \tag{1.4}$$

Here, *shareX* represents the share of the population subgroup of interest in the overall population. $MobileCoverage_{\text{it=0}} \times shareX_{\text{it=0}}$ is an interaction of two continuous variables.

[13]Information with regards to free telephony for the Austrian market can, for example, be found here: `https://www.gis.at/befreien/fernsprechentgelt/`; in German, last accessed February 7, 2018.

A positive estimate on β_3 would imply that the greater the share of the population group, X, under investigation, the stronger the effect of mobile coverage on A1 fixed-line penetration decline. Or the other way around: A positive estimate on β_3 would imply that the higher mobile coverage, the stronger is the effect of the share of the population group under investigation on our outcome variable. Importantly, in a model with continuous by continuous interactions, coefficient estimates on the main effects, β_2 and β_4 are reflecting conditional relationships. For example, the estimate on β_2 is the effect of mobile coverage on A1 fixed-line penetration decline, conditional on the share of the population group investigated being zero. This can be easily seen by plugging this zero into Equation (1.4). In what follows, we skip control variables for the ease of exposition:

$$\begin{aligned}\Delta(\ln FL_{\text{it=1,it=0}}) =& \alpha_L + \beta_2 MobileCoverage_{\text{it=0}} + \beta_3 MobileCoverage_{\text{it=0}} \times 0_{\text{it=0}} + \beta_4 0_{\text{it=0}} + \varepsilon_{\text{it}} \\ =& \alpha_L + \beta_2 MobileCoverage_{\text{it=0}} + \varepsilon_{\text{it}}\end{aligned}$$

while a share of 1 for a specific population group would result in:

$$\begin{aligned}\Delta(\ln FL_{\text{it=1,it=0}}) =& \alpha_L + \beta_2 MobileCoverage_{\text{it=0}} + \beta_3 MobileCoverage_{\text{it=0}} \times 1_{\text{it=0}} + \beta_4 1_{\text{it=0}} + \varepsilon_{\text{it}} \\ =& \alpha_L + (\beta_2 + \beta_3) MobileCoverage_{\text{it=0}} + 1\beta_4 + \varepsilon_{\text{it}}\end{aligned}$$

such that for the population share under investigation being 1, the effect of mobile coverage on the rate of change of A1 fixed-line penetration is $\beta_2 + \beta_3$. Table 1-5 presents the results of the interacted model for the share of elderly. Estimates depicted in the second row illustrate that an increase in the share of elderly significantly reduces the effect of mobile coverage on A1 fixed-line penetration decline. In detail, a one standard deviation increase (three percentage points, see also Table 1-1) in the share of people above 65 years reduces the effect of mobile coverage on A1 fixed-line penetration decline by 0.14 percentage points. Comparing coefficients on the main effect of mobile coverage in row 1 across Columns (1) to (7), we observe that the effect of mobile coverage systematically differs along the distribution of the share of elderly above 65 years. As we move along the percentiles of elderly, the effect becomes “less negative”, implying that mobile coverage is only perceived as a substitute to a smaller degree in regions with a high share of elderly population.

Table 1-5: Heterogeneity by Share of Elderly

Dependent Variable: A1 FL p.hh. rate of change	(1) Frac. >65 5th percentile	(2) Frac. >65 10th percentile	(3) Frac. >65 25th percentile	(4) Frac. >65 50th percentile	(5) Frac. >65 75th percentile	(6) Frac. >65 90th percentile	(7) Frac. >65 95th percentile
Mobile Coverage	-0.456***	-0.423***	-0.354***	-0.273***	-0.175**	-0.0748	-0.00564
	(0.147)	(0.138)	(0.120)	(0.102)	(0.0889)	(0.0884)	(0.0961)
Mobile Coverage x Frac. > 65	0.140***	0.140***	0.140***	0.140***	0.140***	0.140***	0.140***
	(0.0495)	(0.0495)	(0.0495)	(0.0495)	(0.0495)	(0.0495)	(0.0495)
Frac. > 65	-0.129***	-0.129***	-0.129***	-0.129***	-0.129***	-0.129***	-0.129***
	(0.0442)	(0.0442)	(0.0442)	(0.0442)	(0.0442)	(0.0442)	(0.0442)
Kleibergen-Paap F-statistic	16.83	16.83	16.83	16.83	16.83	16.83	16.83
Two digit FE	X	X	X	X	X	X	X
N	2058	2058	2058	2058	2058	2058	2058

Notes: Mobile Coverage represents the average fraction of households that is covered by 2G and 3G networks. Frac. ≥ 65, the share of elderly, is rescaled to have a standard deviation of 1 in all specifications and a particular percentile of zero throughout Columns (1) to (7). In Column (1), the 5th percentile of Frac. ≥ 65 is equal to zero, in Column (2) the 10th percentile is equal to zero, etc. Heteroscedasticity robust standard errors in parentheses. Significance levels: * $p<0.10$, ** $p<0.05$, *** $p<0.01$. *Data sources:* A1 Telekom Austria, Statistik Austria and GfK GeoMarketing GmbH.

1.5.3 Robustness Checks

In order to test the robustness of our results with regard to the inclusion of different (sized) postal code areas, we leave out the five major cities in Austria from the estimation in Column (2) of Table 1-6. For comparison, Column (1) presents the baseline IV estimate from Table 1-3, Column (5). The decline in fixed-line penetration is slightly stronger in Column (2). However, the similar magnitude of the coefficient alleviates concerns that the effect is driven only by major cities or solely rural areas. In Column (3) of Table 1-6, we trim the sample by the top and bottom decile, instead of percentile, to make sure the results are neither driven by the upper nor the lower end of the distribution. Again the decline of fixed-lines between 2011 and 2014 is not qualitatively different from the baseline IV results in Column (1).

1.6 Conclusion

In this paper, we present a novel approach to estimate substitution between alternative technologies, in our case between mobile and fixed-line telephony. Instead of estimating cross-price elasticities, we estimate cross-technological elasticities depending on the availability and quality of mobile access. For this, we use fine grained regional data in Austria. The two major advantages of our approach are that, first, we do not need information on mobile prices that are hard to measure and, second, we can take into account heterogeneity of (postal code) regions with regard to the availability of alternative technologies.

However, as regional variation in the availability of alternative technologies may in itself be endogenous, we use an instrumental variable approach that exploits geographical peculiarities in the Austrian surface contour that cause exogenous variation in mobile coverage. We find that an increase in local mobile coverage has a significant positive effect on fixed-mobile substitution: a one percentage point increase in the availability of mobile coverage causes the rate of change in fixed-line usage to decrease by an additional 0.3 percentage points between 2011 and 2014. This implies that fixed-lines and mobile are technological substitutes.

Table 1-6: Robustness Checks

Dependent Variable: A1 FL p.hh. rate of change (2011-2014)	Overall	w/o top 5 cities	w/o top/bottom decile
Mobile Coverage	-0.285***	-0.306***	-0.267***
	(0.100)	(0.101)	(0.0857)
Log of FL p.hh. 2011	0.0246***	0.0226**	0.0107
	(0.00904)	(0.00933)	(0.00825)
Dist. Highway (in km)	0.000649**	0.000642**	0.000432**
	(0.000252)	(0.000256)	(0.000203)
Dist. Railway (in km)	0.000612	0.000434	-0.000340
	(0.000702)	(0.000695)	(0.000606)
$1-3$ alternative FL operator	0.000679	0.00183	0.00349
	(0.00543)	(0.00573)	(0.00473)
≥ 4 alternative FL operator	-0.00701	-0.00462	-0.00388
	(0.00686)	(0.00732)	(0.00591)
Fraction Students 2011	-0.0715	0.0403	-0.137
	(0.226)	(0.237)	(0.200)
Fraction >65 2011	-0.299***	-0.319***	-0.349***
	(0.107)	(0.109)	(0.0963)
Fraction Female 2011	0.0831	0.0572	0.217
	(0.224)	(0.225)	(0.192)
Fraction Foreigners 2011	-0.142***	-0.125**	-0.0541
	(0.0474)	(0.0498)	(0.0416)
Fraction Unemployed 2011	0.163	0.212*	0.135
	(0.109)	(0.111)	(0.0892)
Fraction Secondary Educ. 2011	-0.0138	-0.00325	0.0180
	(0.0580)	(0.0608)	(0.0527)
Fraction Tertiary Educ. 2011	0.139*	0.140	0.0733
	(0.0776)	(0.0875)	(0.0662)
First stage (Dependent Variable: Mobile Coverage)			
TRI	-0.576***	-0.59***	-0.508***
	(0.146)	(0.157)	(0.141)
Kleibergen-Paap F-statistic	30.17	28.46	19.64
Two Digit FE	X	X	X
N	2058	1969	1679

Notes: Mobile Coverage represents the average fraction of households that is covered by 2G and 3G networks. Heteroscedasticity robust standard errors in parentheses. Significance levels: * p<0.10, ** p<0.05, *** p<0.01. *Data sources:* A1 Telekom Austria, Statistik Austria and GfK GeoMarketing GmbH.

Our paper makes three main contributions. First, we provide evidence regarding the substitutability of mobiles and fixed-lines, employing a new method, finding evidence for substitution effects. In addition, we show that there is substantial heterogeneity of (postal code) regions with respect to the availability of alternative technologies and that this heterogeneity significantly affects competition and consumer decisions. Third, we present a new approach to estimate substitution between alternative technologies that is not limited to the estimation of substitutability of fixed-lines and mobiles.

Chapter 2

Returns to ICT Skills*

2.1 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 Inter-

*This chapter is joint work with Oliver Falck and Simon Wiederhold. An earlier version of this chapter is available as CESifo Working Paper No. 5720. For acknowledgements, please refer thereto.

[1] `http://www.getonlineweek.eu/vice-president-neelie-kroes-says-digital-literacy-and-e-skills-are-the-new-literacy/`; last accessed January 8, 2018

[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.

net 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 identify returns to ICT skills based on differences in ICT skills and wages between age cohorts within countries.

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

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

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 wages.[4] We also show that households in Germany without broadband Internet access do not selectively relocate to regions where broadband is available.

Perhaps most importantly, 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. There is substantial evidence that broadband affects growth and productivity (e.g., Draca, Sadun, and Van Reenen, 2009; Czernich, Falck, Kretschmer, and Woessmann, 2011). Direct wage effects of broadband would raise concern for identification in the international analysis only if they would be asymmetric across age cohorts, because our IV analysis exploits variation based on differences in the effect of exogenous broadband availability on ICT skills across age cohorts. However, such age pattern in direct broadband effects cannot be ruled out a priori because there is widespread evidence that certain groups – namely, highly-educated workers and young workers – benefit disproportionally from broadband (e.g., Autor and Dorn, 2009; Atasoy, 2013; Akerman, Gaarder, and Mogstad, 2015. We thus show that the most prominent channels of direct productivity effects of broadband (increasing firm productivity through the adoption of broadband, introduction of online job search channels improving the quality of job match-

[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.

ing) do not exhibit the same non-linear age pattern as our first stage. Moreover, we can even control for direct productivity effects of broadband within countries or country-industry cells that are linear in age.

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]

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

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

[7] See Draca, Sadun, and Van Reenen (2009) for a recent review.

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.

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

[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.

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

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 2.2 describes the PIAAC data and the assessment of ICT skills. Section 2.3 outlines our two IV strategies. Section 2.4 presents the returns-to-ICT-skills estimates. Section 2.5 provides an analysis of the validity of our instruments, followed by various robustness checks in Section 2.6. Section 2.7 investigates whether occupational selection explains positive returns to ICT skills. Section 2.8 concludes and derives some implications for policy-making.

2.2 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 Au-

[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.

gust 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 (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 prac-

[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.

[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.

tical tasks" (OECD, 2013b, 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 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]

[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 (2013b) for details.

[17] See OECD, (2013b, p. 89, 2015, p. 39) 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.

[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 2.6 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 (2013b), 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.

We also drop individuals aged 16–19 years because most have not finished their education. Moreover, our identification strategy (see Section 2.3) 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 2-1 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, 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 2-2 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.

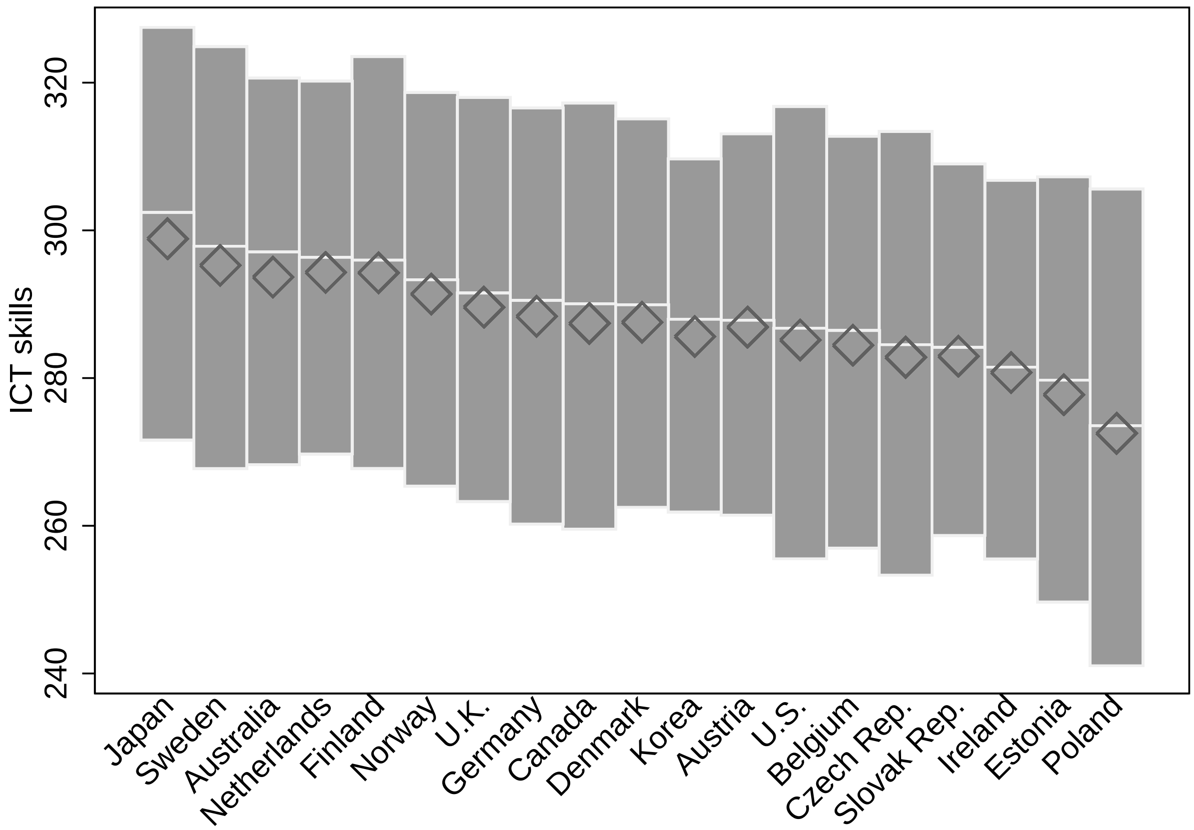
[21] Placebo tests and robustness analyses (see Sections 2.5 and 2.6) show the appropriateness of these sample restrictions.

[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.

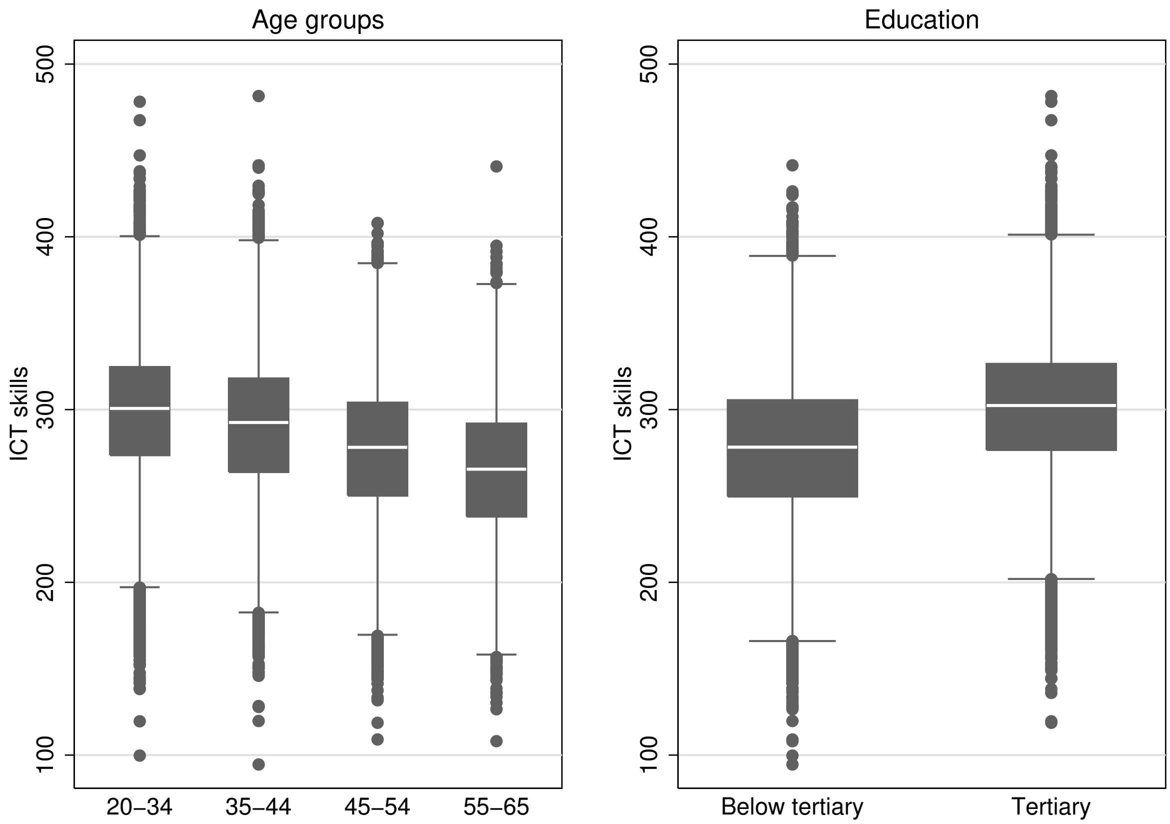
Figure 2-1: ICT Skills Around the World



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.

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.

Figure 2-2: 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.

In the econometric analysis, we standardize ICT skills to have mean zero and SD one[25] 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.

2.3 Identification Strategy

2.3.1 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:

$$\log w_{\mathrm{ic}} = \beta_0 + \beta_1 ICT_{\mathrm{ic}} + \boldsymbol{X}_{\mathrm{ic}}\boldsymbol{\beta_2} + \mu_{\mathrm{c}} + \varepsilon_{\mathrm{ic}} \tag{2.1}$$

w_{ic} is gross hourly wages earned by individual i living in country c and ICT_{ic} are the individual's ICT skills.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. For instance, since the ICT-based applications included in the PIAAC test are unfamiliar to the respondents, they may have problems solving the tasks even if they are perfectly capable of using ICT at their workplace. Errors in the measurement of ICT skills can also occur if PIAAC respondents had a bad testing day or solved tasks correctly or incorrectly simply by chance. This measurement error in the assessment of an individual's ICT skills will bias the coefficient on ICT skills toward zero.[29] Moreover, higher earnings may actually lead to improvements in ICT skills, giving rise to the problem of reverse causality. Better jobs may more likely require and reinforce skills or they may provide

[27] In Section 2.5.1, 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.

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.

2.3.2 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. With the liberalization of the telecom sector, many countries implemented a universal service obligation, forcing one or more telecommunication carriers to provide their services at affordable prices regardless of households' geographic location. The extent to which countries imposed such universal service obligation largely determined a country's fixed-line penetration.

[30] The major alternative fixed-line access technology is broadband access via cable TV networks (see Section 2.5.2).

[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".

The copper wires – which were solely used for fixed-line voice calls before the emergence of DSL technology – could be upgraded to provide DSL by installing new hardware (so called DSLAMs) at the MDFs, making data traffic at high bandwidths to the telecommunication carrier's backbone network feasible (see Figure 2-3). This technological feature of DSL technology made broadband rollout substantially cheaper compared to having to roll out new wires to households. Even in countries where fiber was rolled out to the curbs or homes, the existing ducts of traditional fixed-line networks were used to reduce the deployment cost of broadband. Thus, the existing fixed-line infrastructure initially built for purposes other than the provision of broadband allowed for an economically viable widespread 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 2.3.3).

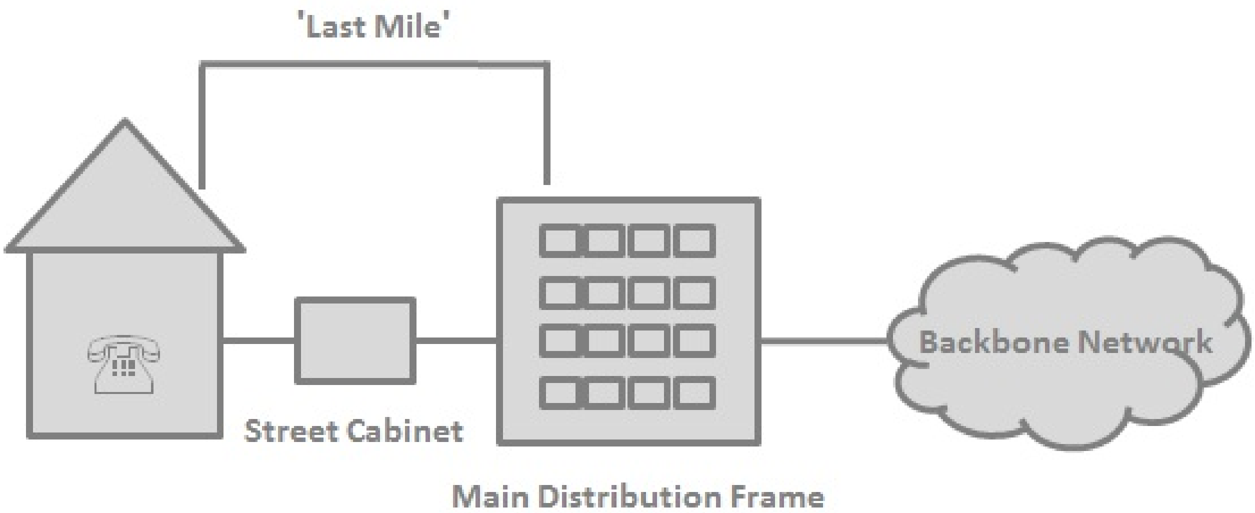
At the same time, the reliance of broadband rollout on traditional voice-telephony networks led to an uneven distribution of broadband Internet access within countries in the early years of the Internet era. While the distance between the household and the MDF, the so-called last mile (see Figure 2-3), 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 2.3.4).

2.3.3 Cross-Country Instrumental-Variable Model

We begin by showing that preexisting fixed-line infrastructure affected the introduction and initial diffusion of broadband Internet. Figure 2-4 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 2-5 shows a strong positive relationship between preexisting fixed-line diffusion and broadband diffusion in 2006,

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

Figure 2-3: 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.

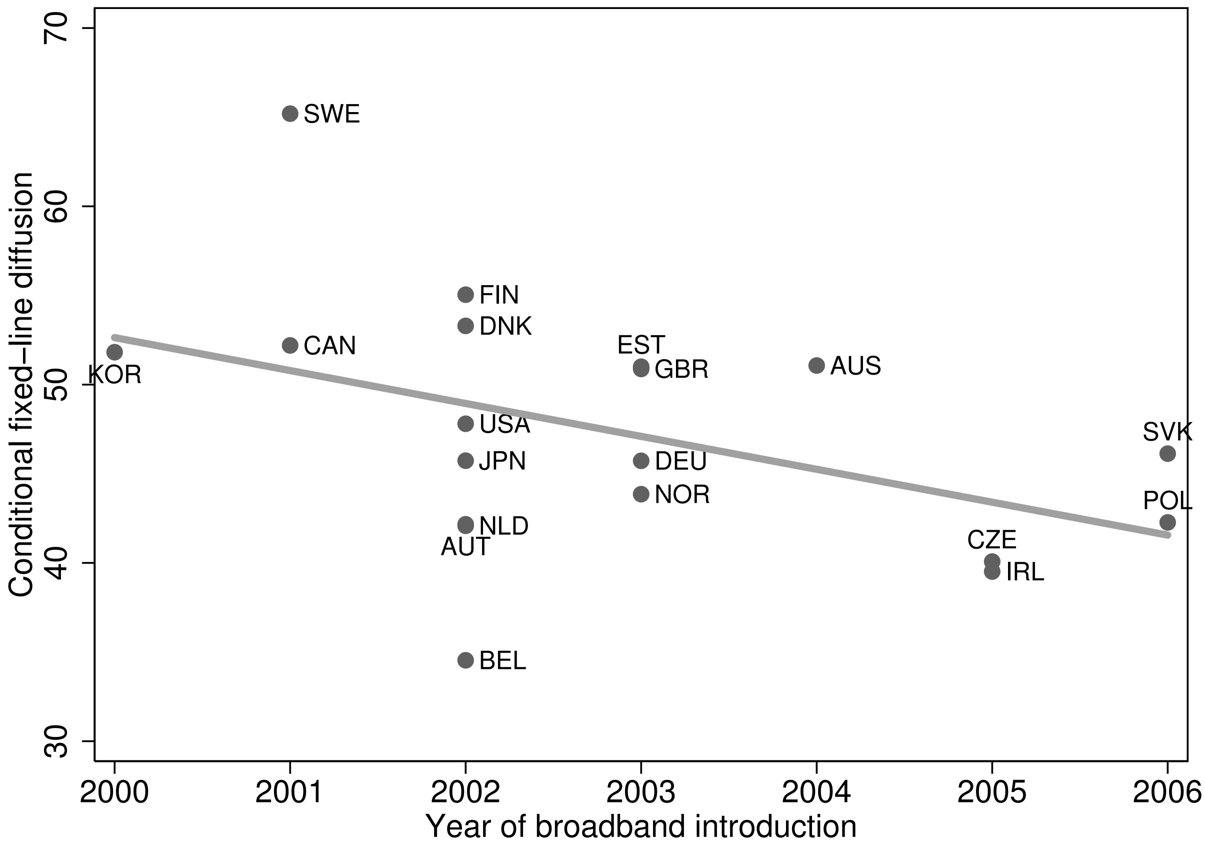
that is, several years after the first introduction of broadband.[33] Both figures indicate that broadband infrastructure relies on traditional fixed-line networks.

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 2-5). 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]

[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

Figure 2-4: Effect of Fixed-Line Diffusion on Broadband Introduction

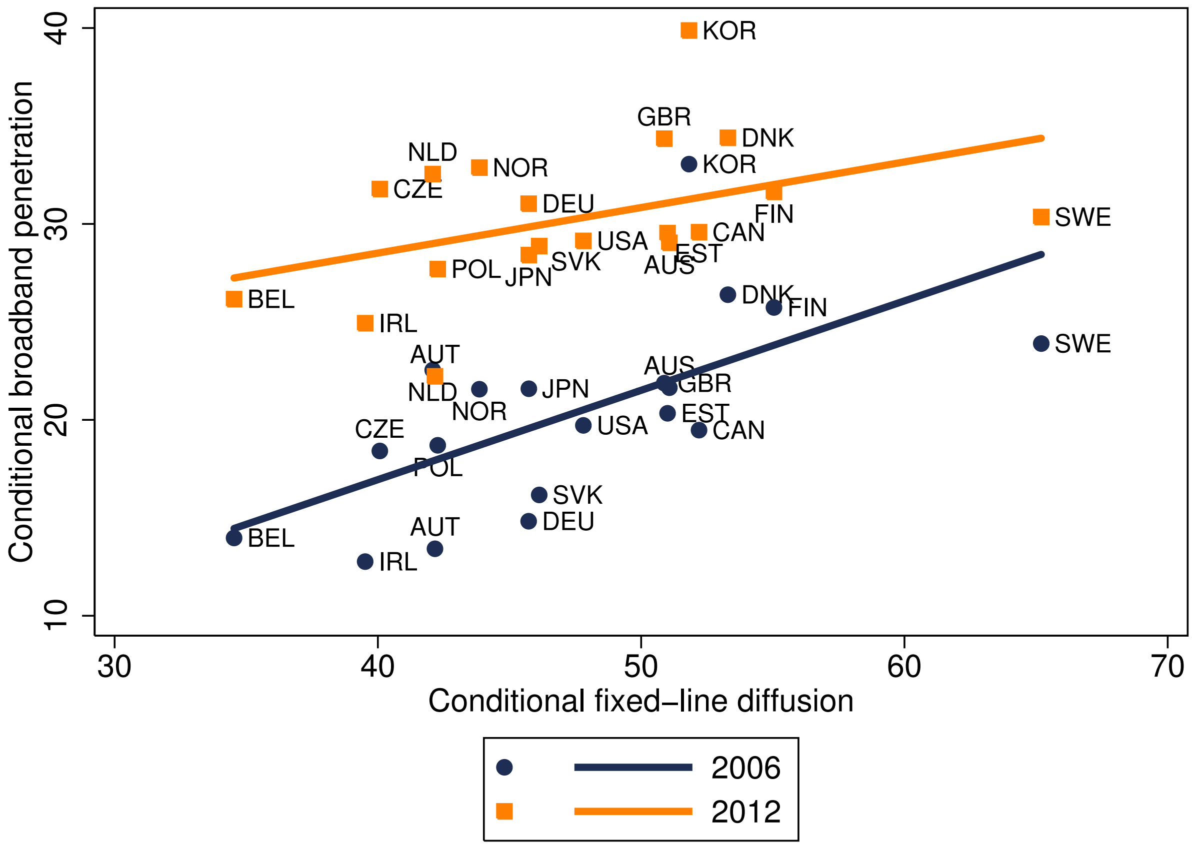


Notes: Graph shows the relationship between fixed-line diffusion in 1996 (conditional on control variables) and first emergence of broadband in a country. Fixed-line diffusion is the number of telephone access lines per 100 inhabitants in 1996. Year of broadband introduction in this graph is the year when broadband penetration (i.e., the number of broadband subscriptions per inhabitant) first exceeded 5 percent. Control variables are GDP per capita in 1996 (in logs), years of schooling in 1995, population size in 1995, and cable TV diffusion (measured as cable television subscriptions per inhabitant) in 1996. *Data sources:* Barro and Lee (2010), ITU, OECD.

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

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.

Figure 2-5: 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 100 inhabitants in 1996. Control variables are GDP per capita in 1996 (in logs), years of schooling in 1995, population size in 1995, and cable TV diffusion (measured as cable television subscriptions per inhabitant) in 1996. *Data sources:* Barro and Lee (2010), ITU, OECD.

speed was 128 kbit/s. The bandwidth increased substantially with the emergence of broadband, reducing limitations to Internet use as well as the excessive waiting times for loading web pages. According to a study by the Pew Internet and American Life Project (2002), even simple activities such as writing an e-mail are carried out more often when broadband access instead of dial-up technology is available in a household (52 vs. 67 percent). The advantage of fast Internet access is even more pronounced for information-seeking activities (13 vs. 30 percent), also including job-related research (14 vs. 36 percent). We therefore expect that primarily the availability of broadband Internet (vis-à-vis Internet access via dial-up technology) induces learning-by-doing effects in the accumulation of ICT skills. Note, however, that Internet use beyond the mere consumption of content (e.g., podcasting, blogging, social networking), as prevalent the second half of the 2000s, is less likely to contribute to the learning-by-doing effects we identify.

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 2-6 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 2-6 is very similar when adjusting ICT skills by the age-specific SD to avoid potential ceiling effects (results available upon request).

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 2.1) is the predicted value of the following first-stage model:

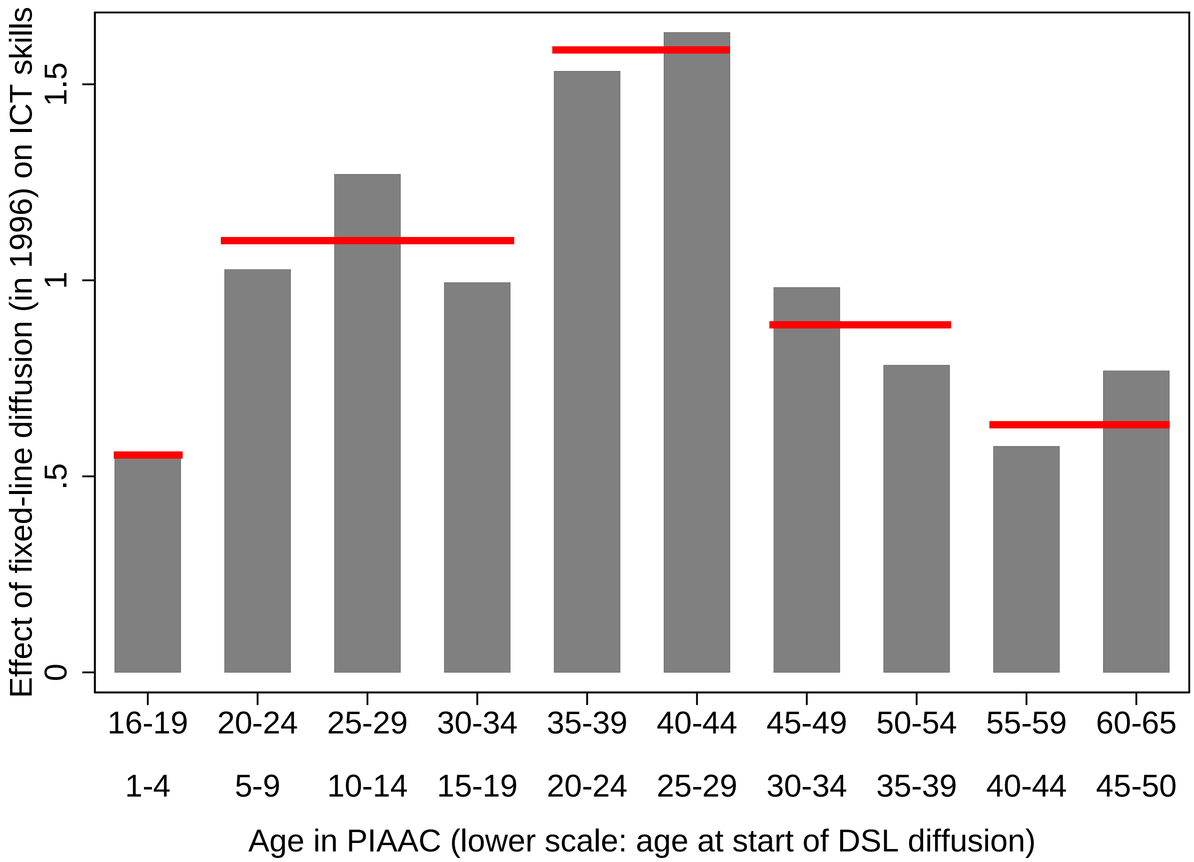
$$ICT_{\mathrm{ic}} = \alpha_0 + \sum_a \alpha_1 a_{\mathrm{ic}} \times FD_{\mathrm{c}} + \boldsymbol{X}_{\mathrm{ic}}\boldsymbol{\alpha_2} + \mu_{\mathrm{c}} + \vartheta_{\mathrm{ic}} \tag{2.2}$$

[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.

Figure 2-6: 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.

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 X_{ic} contains the individual-level control variables from Equation 2.1 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

[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.

ICT skills (first stage) or wages (second stage) is not identified. ϑ_{ic} is the error term of the first-stage equation.[39]

The IV model in Equation 2.2 exploits the fact that the ICT skills of different age cohorts within each country benefit differently from early (exogenous) broadband access. Using only age-induced variation within countries addresses two major concerns. First, it captures any direct positive economic effect of the traditional fixed-line infrastructure on current wage levels. In fact, Roeller and Waverman (2001) show that a significant portion of economic growth in OECD countries between 1971 and 1990 can be attributed to telecommunications. Second, it controls for a potential correlation of baseline fixed-line networks with baseline levels of wealth, technology, education, institutions, skills, and so forth, all of which may affect today's ICT skills and wages.

However, key to our identification strategy is that the effect of any omitted variables does not follow the same inverted-U-shaped age pattern as the effect of exogenous broadband availability does. This assumption may fail to hold if omitted variables affect younger and older workers differently. Thus, Sections 2.5.2 and 2.5.3 provide comprehensive evidence that our results cannot be attributed to country-cohort specific factors. We can even allow for differential age trends by country, which addresses the concern that productivity and wages of young workers may benefit disproportionally from broadband (e.g., Autor and Dorn, 2009).[40]

2.3.4 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

[39] We report Huber-White heteroskedasticity-robust standard errors. The obvious alternatives would be to cluster standard errors at the country level (i.e., the level where fixed-line diffusion varies) or to use two-way clustered standard errors to account for correlated standard errors at the levels of country and age. Results are robust when we cluster standard errors. However, we use heteroskedasticity-robust standard errors in the main specification because recent research has shown that clustered standard errors can provide misleading inferences in samples with a small number of clusters (e.g., Donald and Lang, 2007; Cameron, Gelbach, and Miller, 2008; Angrist and Pischke, 2009; Imbens and Kolesar, 2016). Although there is no widely accepted threshold when the number of clusters is "small", the work of Cameron, Gelbach, and Miller (2008), Angrist and Pischke (2009), and Harden (2011) suggests a cutoff of around 40 clusters. Since there are only 19 clusters in our cross-country sample, clustering may be problematic in our case. As an alternative to clustering, we also use the wild bootstrap procedure suggested by Cameron, Gelbach, and Miller (2008) for improved inference with few clusters (using Stata's cgmwildboot command for implementation). Results remain robust when employing wild bootstrapping.

[40] Unfortunately, there were no earlier PIAAC surveys, which precludes a direct investigation of how ICT skills and wages of workers in different age cohorts developed before broadband Internet became available (i.e., in absence of the "treatment").

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 2.3.2). 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.[41] 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.[42] Past this threshold, DSL technology was no longer feasible without replacing parts of the copper wire (typically placed between the MDF and the street cabinet) with fiber wire (see Figure 2-3). 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.[43]

[41] 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.

[42] 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, 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.

[43] 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).

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 2-7 shows the share of households with access to DSL between 2005 and 2009 in municipalities below and above the 4,200-meter threshold.[44] 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.

The first-stage model in the within-Germany analysis is a municipality-level (m) version of Equation 2.2, 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:

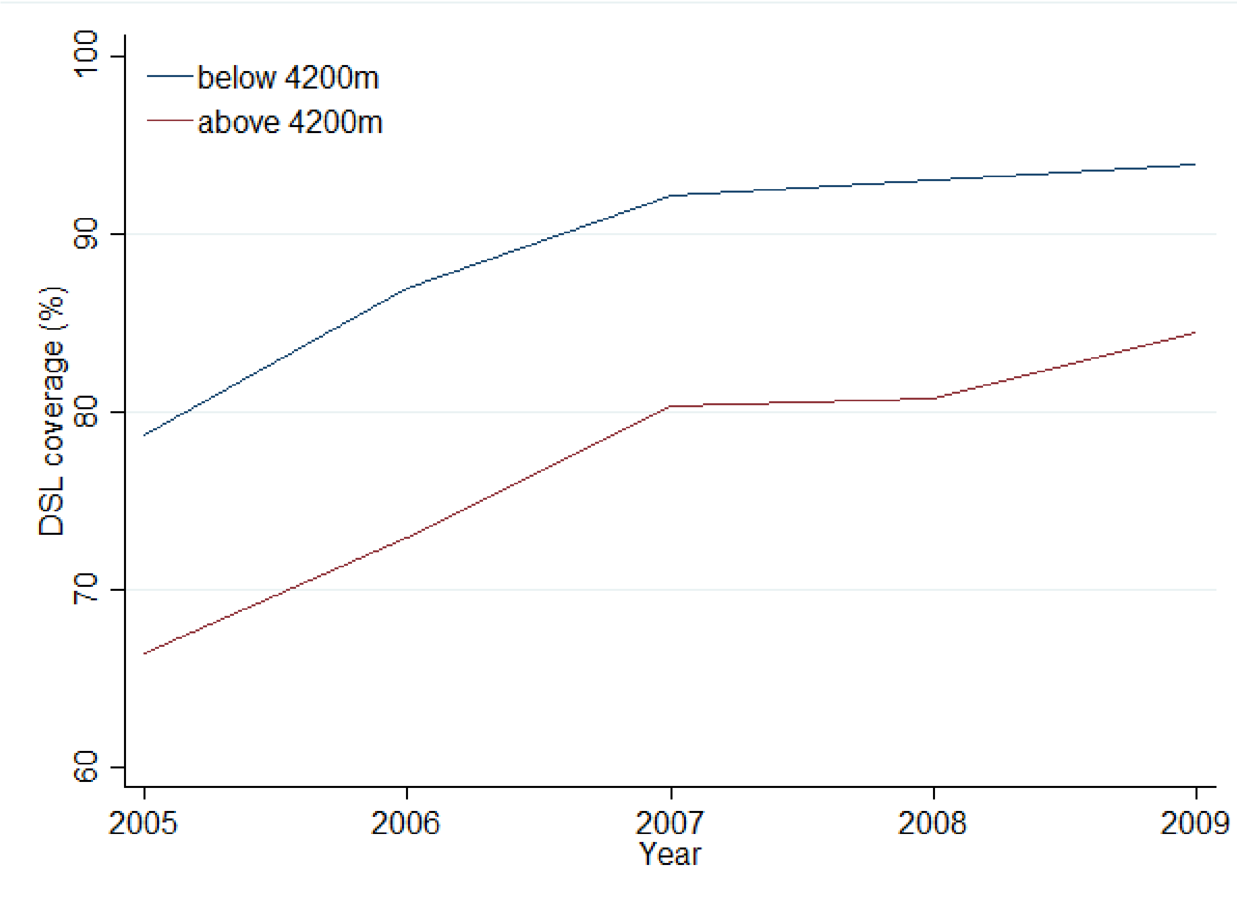
$$ICT_{\mathrm{im}} = \alpha_0 + \alpha_1 T_{\mathrm{m}} + \boldsymbol{X}_{\mathrm{im}}\boldsymbol{\alpha_2} + \boldsymbol{X}_{\mathrm{m}}\boldsymbol{\alpha_3} + \vartheta_{\mathrm{im}} \tag{2.3}$$

The vector X_{im} includes a quadratic polynomial in work experience and gender.[45] Since we cannot include municipality fixed effects in this specification, the vector X_{m} contains controls for a municipality's economic situation prior to emergence of broadband by including

[44] 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.

[45] This specification follows the baseline model in Hanushek, Schwerdt, Wiederhold, and Woessmann (2015). In Section 2.6, 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).

Figure 2-7: 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.

municipality-level unemployment rate and the local age structure, both measured in 1999 (broadband first emerged in 2000 in Germany).[46] ϑ_{im} is the error term.[47]

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 loca-

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

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

tions 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).

2.4 Returns to ICT Skills

2.4.1 International Evidence

We now estimate the causal effect of ICT skills on individuals' wages. Columns (3) and (4) of Table 2-1 present the results from our cross-country IV model. In the lower panel of Table 2-1, we report the first-stage coefficients and the F statistic on the excluded instruments.[48] 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.[49] 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 2-1 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

[48] 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 (Cragg and 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 2-1.

[49] Complete first-stage results can be found in Table A-2.

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)).

Both IV coefficients are about twice as large as the corresponding OLS results, shown in Columns (1) and (2) of Table 2-1. These higher returns in the IV specification are likely attributable to measurement error in ICT skills, biasing our results toward zero (see Section 2.3.1), 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., Card, 2001; Kling, 2001), we explore potential differences in the age pattern of early broadband access for different levels of ICT proficiency.[50] The OECD distinguishes three different ICT-proficiency levels: low (level 1 and below), intermediate (level 2), and high (level 3) (OECD, 2013b). 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).[51] OLS regressions show that the complier population has particularly high returns to ICT skills (see Table A-3, Column 1).[52] Another reason for a local average treatment effect (LATE) to arise in the IV regressions is that our instruments isolate a specific dimension of ICT skills, namely,

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

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

[52] A potential reason for these high returns is occupational selection. We will come back to this issue in Section 2.7.

Internet skills. These are likely scarcer than overall ICT skills (that also include computer proficiency) and are therefore rewarded higher in modern labor markets.

Table 2-1: Returns to ICT Skills: International Evidence

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

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

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 participating in the study.[53] 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.[54] 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.[55] 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.[56]

2.4.2 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 2-2, we present results from IV regressions using as instrument a dummy variable that equals 1 for municipalities with distances between the municipality centroid and the assigned MDF above the threshold of 4,200 meters. In the full sample, shown in Columns (5) and (6), the first-stage results indicate that persons in municipalities above the 4,200-meter threshold have substantially lower ICT skills than per-

[53] 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.

[54] 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 Keueger (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.

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

[56] The estimates in Table 2-1 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)).

sons 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.[57] 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.[58] Although we do not find evidence that the mobility pattern is systematically related to our instrument (see Section 2.5.4), it is a source of measurement error decreasing instrument strength.[59]

Turning to the second stage of our IV estimation in the upper panel of Table 2-2, 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.[60] 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).[61]

[57] Table A-4 provides the complete first-stage results.

[58] 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 2-2 to judge instrument strength.

[59] 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, Rubin et al., 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).

[60] 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 Schönberg (2009) and Card, Heining, and Kline (2013).

[61] 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.

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

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

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

2.5 Assessing the Identification Strategy

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

International Analysis. To interpret the IV results in Section 2.4 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 2.3.3, 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 2-3: 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 × age 20–34	0.184*	–0.125	0.141	0.190*	–0.124	0.147	–0.789
	(0.099)	(0.095)	(0.103)	(0.099)	(0.095)	(0.103)	(0.508)
Fixed-line diffusion × age 35–44	0.107	–0.063	0.313***	0.121	–0.060	0.305***	–0.865*
	(0.103)	(0.100)	(0.108)	(0.103)	(0.099)	(0.108)	(0.502)
Fixed-line diffusion × age 45–54	–0.029	–0.024	0.121	–0.024	–0.024	0.117	–0.571
	(0.107)	(0.103)	(0.110)	(0.107)	(0.102)	(0.110)	(0.489)
ICT skills	0.675***	0.737***					
	(0.004)	(0.004)					
Numeracy skills			0.332***				
			(0.007)				
Literacy skills			0.549***				
			(0.007)				
Individual characteristics	X	X	X	X	X	X	X
Country fixed effects	X	X	X	X	X	X	X
R squared (adjusted)	0.58	0.63	0.67	0.10	0.04	0.10	0.09
Individuals	53,879	53,879	53,879	53,879	53,879	53,879	6,298

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

Table 2-3 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)).[62] However, there is still an inverted-U-shaped age pattern in the effect of the traditional fixed-line network on ICT skills when controlling for numeracy and literacy skills (Column (3)). Arguably, controlling for ICT skills is problematic because the instruments affect ICT skills, making it an endogenous variable in the numeracy and literacy regressions. However, results are very similar when we net out the effect of ICT skills on numeracy and literacy skills ex ante by using residualized skill scores (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 2-3 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 2-1 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.

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 2-4 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 2-5 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.

[62] 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.

Table 2-4: 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	–0.020	–0.139***	0.038	–0.025	–0.128***
	(0.054)	(0.065)	(0.047)	(0.055)	(0.065)	(0.047)
ICT skills	0.713***	0.772***				
	(0.018)	(0.017)				
Numeracy skills			0.330***			
			(0.032)			
Literacy skills			0.516***			
			(0.032)			
Individual characteristics	X	X	X	X	X	X
Municipality characteristics	X	X	X	X	X	X
R squared (adjusted)	0.59	0.63	0.68	0.05	0.01	0.06
Individuals	1,849	1,849	1,849	1,849	1,849	1,849
Municipalities	204	204	204	204	204	204

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

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

2.5.2 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.

Table 2-5: Within-Germany Evidence: Placebo Tests Using Migration Status

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

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

A major concern is that broadband is directly productive for firms, affecting wages of workers irrespective of their own usage of ICT skills. One may argue that when firms get broadband Internet earlier (or cheaper), they will invest more in capital that is complementary to this technology. Even in the most extreme case of no learning-by-doing effects in the accumulation of ICT skills, returns to ICT skills may still change as a result of a ICT capital-skill complementarity, and there is no a priori reason to believe that the level of this complementarity is the same for different cohorts. In Column (2) of Table 2-6, we assess whether broadband affects workers' wages due to the accumulation of ICT capital (vis-à-vis ICT skills) by controlling for country-level ICT capital (in 2012) interacted with age cohorts. We still observe learning-by-doing effects – the interactions of fixed-line diffusion with age in the first stage are very similar to those in the baseline (Column (1))[63] – and estimated returns to ICT skills remain statistically significant and sizeable. As expected, the coefficient on ICT skills decreases compared to the baseline because investment in ICT capital is likely one channel through which returns to ICT skills materialize. Thus, while our results suggest that there is indeed a ICT capital-skill complementarity, it is unlikely that potential direct productivity effects of ICT capital invalidate the exclusion restriction.

Another way to account for direct productivity effects of broadband is to control for alternative broadband access technologies which did not induce learning-by-doing effects in ICT skills. As noted in (Czernich et al., 2011), broadband rollout is also determined by the spread of the cable TV network before broadband was introduced. However, preexisting cable TV diffusion should not exhibit learning-by-doing effects of a substantive magnitude due to a direct "distraction effect" from watching TV. For instance, data from American Time Use Survey reveal that in 2003 the average American spent 2.58 hours per day in front of the TV but only spent 0.08 hours per day on the phone. Therefore, the direct distraction effect of the cable TV network is likely far higher than that of voice telephony. In line with this reasoning, we find no significant age pattern in the effect of traditional cable TV diffusion on ICT skills (see first stage in Column (3) of Table 2-6). Controlling for a potential age pattern in direct productivity effects of broadband induced by traditional cable TV networks in Column (3) also barely changes the baseline returns to ICT skills.

In Section 2.3.3., 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

[63]Column (1) of Table 2-6 shows the baseline results in the full sample of 19 countries. We could not obtain data on ICT capital in two countries, Germany and Poland. However, first-stage and second-stage results in the smaller sample are very similar to those in the full sample (e.g., returns to ICT skills are 0.214 vs. 0.236 in the full sample).

Internet and build up ICT skills. We further argued that if mobile technologies are primarily used by younger persons, it may partly explain why we observe relatively small effects of exogenous fixed-line broadband diffusion on the ICT skills of persons in the younger age cohorts in PIAAC. Column (4) of Table 2-6 shows that the effect of mobile telephone diffusion[64] on ICT skills indeed decreases steadily in age, with ICT skills of persons aged 20–34 benefitting by far the most from mobile Internet access.[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 (5)).

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.

[64]The diffusion of mobile telephones has mainly enabled the provision of wireless broadband services (OECD, 2013a). 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).

[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.

Table 2-6: ICT Capital and Alternative Broadband-Access Technologies

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

Notes: Two-stage least squares regressions weighted by sampling weights (giving same weight to each country). Sample: employees aged 20–65 years, no first-generation immigrants. Dependent variable in second stage is *log gross hourly wage*, measured in PPP-USD. Column (1) replicates the baseline model in Column (4) of Table 2-1. *Fixed-line diffusion:* voice-telephony penetration rate (telephone access lines per inhabitant). *ICT capital:* ICT equipment net fixed assets (System of National Accounts 2008, in current prices) from the OECD National Accounts Statistics; data are not available in Germany and Poland. *Cable TV diffusion:* cable television subscriptions per inhabitant. *Mobile diffusion:* mobile-cellular telephone subscriptions per inhabitant. Omitted age category is 55–65 years. Individual characteristics are age cohorts and gender. Robust standard errors in parentheses. Significance levels: * p<0.10, ** p<0.05, *** p<0.01. *Data sources:* ITU, OECD, PIAAC.

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.[66] To address this issue, we reweight individuals in our sample so that the share of high-skilled individuals is the same in each age cohort within a country. We restrict the sample to workers aged 30 years or more to ensure that we do not misclassify workers because they had not yet finished their university education. The results of this exercise are shown in Column (2) of Table 2-7. Estimated returns (23 percent) are somewhat larger than the baseline estimate using the original PIAAC weights (18 percent), and remain statistically significant.[67]

In Column (3), 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 2-1).[68]

[66] 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.

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

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

Table 2-7: International Evidence: Accounting for the Different Educational Compositions Across Age Groups

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

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

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 2-5 revealed that preexisting fixed-line networks are a good predictor of early broadband Internet penetration but do not well explain contemporaneous diffusion. In other words, our instruments induce variation in ICT skills that stems more from early differences than from contemporaneous differences in broadband penetration. Therefore, direct productivity and wage effects from contemporaneous broadband Internet use in firms should be unrelated to our instruments.

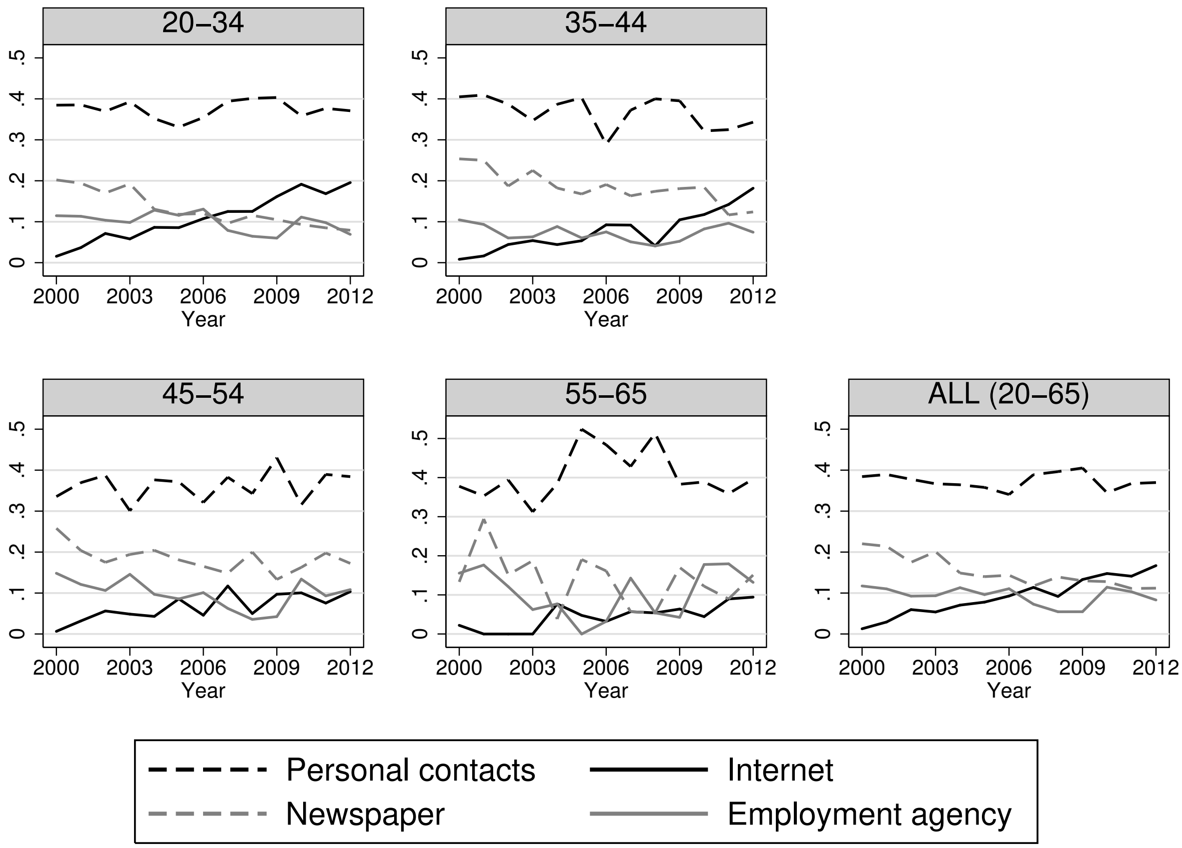
It would also be a threat to our identification strategy if online job search improved job matching, rendering workers more productive. However, although online job markets were introduced during the early phase of broadband diffusion, they were not widely used in the period 2000–2012. Employing annual household survey data from the German Socio-Economic Panel (SOEP) (Wagner, 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 2-8). 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 2-8 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.

However, although, on average, there may be no direct effect of broadband availability on wages through improved job matching, online job search may lead to higher wages for some age groups (e.g., younger workers). We test for age effects in the relationship between online job search and wage growth between jobs by again employing the SOEP data. We construct a sample of individuals with job-to-job transition(s) between 2000 and 2012 who

[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.

Figure 2-8: 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).

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 2-8. 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.

2.5.3 Exclusion Restriction: Age-Specific Direct Wage Effects of Broadband

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

[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.

Table 2-8: Does Online Job Search Affect Wages?

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

Notes: Least squares regressions pooling the years 2000–2012. Sample: German employees aged 20–65 years (in the respective year) with a job-to-job transition. Dependent variable in Columns (3) and (4), *wage growth*, is 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 2-9 tests whether our results are potentially confounded by country-specific and/or industry-specific age effects in earnings that are correlated with the preexisting fixed-line networks. In Column (1), we add country-specific linear age trends to the baseline model to account for unobserved age effects in earnings (e.g., direct productivity effects of broadband that are linear in age). In this regression, we identify effects using only deviations from the country-level mean age trends in earnings. In Column (2), we replace country-specific age trends with industry-specific age trends, while both are included simultaneously in Column (3). Finally, Column (4) includes a full set of country-by-industry fixed effects (380 in total) and also interacts them with age (another 380 trend variables). This model controls for all confounding factors that are specific to countries and industries, even those that differently affect young and old workers (e.g., differences in firm culture or management practices giving rise to age-biased differential productivity effects of broadband across country-industry cells). At the same time, this very demanding specification accounts for different industrial structures of the economies and even for the country-specific industry composition.

Table 2-9: Country-Specific and Industry-Specific Age Trends

Dependent variable: log gross hourly wage				
	(1)	(2)	(3)	(4)
ICT skills	0.405***	0.289***	0.413***	0.424***
	(0.093)	(0.086)	(0.101)	(0.104)
Country fixed effects [19]	X	X	X	X
Industry fixed effects [21]		X	X	X
Country X industry fixed effects [380]				X
Country-specific linear age trends [19]	X		X	X
Industry-specific linear age trends [21]		X	X	X
Country-industry-specific linear age trends [380]				X
Individual characteristics	X	X	X	X
First stage (Dependent variable: ICT skills)				
Fixed-line diffusion × age 20–34	–0.106	0.234	–0.077	–0.003
	(0.418)	(0.155)	(0.408)	(0.409)
Fixed-line diffusion × age 35–44	0.535*	0.706***	0.503*	0.529*
	(0.286)	(0.165)	(0.280)	(0.282)
Fixed-line diffusion × age 45–54	0.086	0.173	0.075	0.095
	(0.207)	(0.167)	(0.203)	(0.199)
Cragg-Donald Wald F statistic	25.5	24.3	22.8	20.6
Stock&Yogo critical value	9.1	9.1	9.1	9.1
Individuals	53,184	53,184	53,184	53,184

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 industry are also excluded. Dependent variable in second stage is *log gross hourly wage*, measured in PPP-USD. Omitted age category is 55–65 years. Numbers in brackets indicates the number of fixed effects. Individual characteristics are age (linear), age cohorts, and gender. Robust standard errors in parentheses. Significance levels: * $p<0.10$, ** $p<0.05$, *** $p<0.01$. *Data sources:* ITU, PIAAC.

Across specifications, returns to ICT skills remain highly significant and even increase somewhat as compared to the baseline estimate once we include country-specific age trends. This suggests a considerable heterogeneity in the age-earnings relationship across countries which age cohort dummies included in the baseline model (controlling for general age effects in earnings) are not able to pick up. One potential reason for this heterogeneity in the age-earnings profiles are the substantial differences in the degree of earnings inequality across OECD countries (e.g., Hanushek, Schwerdt, Wiederhold, and Woessmann, 2015), reflecting the extent to which countries reward the skills of their populations. In fact, when we add to the baseline specification interactions of a country's level of earnings inequality in 1996 with age cohorts, estimated returns to ICT skills increase to the same magnitude as in Columns (1), (3), and (4) of Table 2-9. Likewise, when we split the sample at the median of pre-broadband earnings inequality, we find larger returns to ICT skills in countries with above-median earnings inequality (results are available on request).

Furthermore, if country-specific age effects would be a first-order concern, the residuals from the baseline regression would systematically deviate from a normal distribution. Figure 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 a country-specific age structure in earnings.

In light of the evidence presented above, we consider it highly unlikely that early access to broadband gives rise to higher relative wages for middle-aged workers (vis-à-vis young workers and old workers) irrespective of their own usage of ICT skills.

2.5.4 Sorting: Selective Internal Migration

In our within-Germany IV model, one of the key threats to identification is that people selectively relocate from dwellings at a distance to the MDF above the 4,200-meter threshold to dwellings below the threshold. To empirically assess this concern, we first draw on data from the German regional statistics that contain information for the universe of West German municipalities (n>8000) in the period 2001–2012. We calculate the annual out-migration rate for each municipality as the number of inhabitants moving out of a municipality in a given year relative to the municipality's total population.[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

[73] We use ArcGIS 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.

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

2.6 Robustness

International Analysis. We now assess the robustness of our estimates to additional controls and changes in the sample. In Tables 2-10 and 2-11, we augment the baseline specification (Column (4) of Table 2-1) with controls for several pre-broadband variables that may still affect today's wage levels, interacted with the age cohorts. In Table 2-10, we include variables

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

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 2-11, 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.

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.

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[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 2-10.

[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.

Table 2-10: 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***	0.342***	0.339***	0.160**	0.249***
	(0.077)	(0.090)	(0.082)	(0.079)	(0.076)
Individual characteristics	X	X	X	X	X
Country fixed effects	X	X	X	X	X
First stage (Dependent variable: ICT skills)					
Fixed-line diffusion × age 20–34	0.428***	0.403**	0.268	0.443***	0.394
	(0.158)	(0.171)	(0.250)	(0.157)	(0.259)
Fixed-line diffusion × age 35–44	0.903***	0.844***	1.107***	0.839***	1.221***
	(0.169)	(0.184)	(0.271)	(0.168)	(0.277)
Fixed-line diffusion × age 45–54	0.362**	0.242	0.344	0.285*	0.395
	(0.172)	(0.186)	(0.268)	(0.171)	(0.282)
Cragg-Donald Wald F statistic	26.0	25.4	26.7	31.1	29.4
Stock & Yogo critical value	9.1	9.1	9.1	9.1	9.1
Individuals	51,612	51,253	44,898	53,030	40,814
Returns in baseline specification	0.218	0.298	0.392	0.219	0.316

Notes: Two-stage least squares regressions weighted by sampling weights (giving same weight to each country). Sample: employees aged 20–65 years, no first-generation immigrants. Dependent variable in second stage is *log gross hourly wage*, measured in PPP-USD. All additional country controls refer to 1996 unless otherwise noted and are interacted with the following age cohorts: 20–34 years, 35–44 years, 45–54 years, and 55–65 years. *%High-tech exports* in Column (1) is high-technology exports as a share of manufactured exports; high-technology exports are the top 10 manufactured products with the highest embodied R&D spending relative to the value of shipments, such as in aerospace, computers, pharmaceuticals, scientific instruments, and electrical machinery (Mani, 2004); data not available for Belgium. *%ICT trade* in Column (2) is measured as the share of ICT goods trade in total trade; data not available for Estonia and refer to 1997 in the Slovak Republic. *%STEM graduates* in Column (3) is the share of STEM graduates in all university graduates; STEM subjects are natural science, medical science, mathematics, computer science, engineering, and architecture; data are unavailable for Estonia, Korea, Poland, and the Slovak Republic. *Computer use* in Column (4) is taken from Autor, 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 2-1) 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 2-11: Further Country-Level Controls from the Pre-Broadband Era: Economic Indicators

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

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

International Analysis and Within-Germany Analysis. In Table 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, 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.[78]

2.7 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 advantage of those workers engaged in nonroutine abstract tasks.[79] 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.[80] The authors ask what

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

[79] 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 Schönberg, 2009; Card, Heining, and Kline, 2013; Autor, 2014).

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

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).[81] 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.[82]

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 abstract, routine, and manual tasks from Goos, Manning, and Salomons (2014).[83] Additionally, we

[81] 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).

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

[83] 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 et al., 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,

also classify occupations by computer use by PIAAC respondents, that is, the frequency of using software, programming language, and spreadsheet tools at work.[84]

Table 2-12 shows the results for the international sample; Table 2-13 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.[85] The magnitudes of the effects are considerable: in the international analysis, a one SD increase in ICT skills leads to a 0.80 SD increase in the abstract intensity of a job (e.g., from a business and administration associate to a business and administration professional or from an assembler to a sales worker). Likewise, the routine task content of jobs decreases by 0.41 SD for a one SD increase in ICT skills (e.g., from a plant and machine operator to a science and engineering associate or from a laborer in mining, construction, and manufacturing to a health professional).

To further explore the interpretation of our IV results as local average treatment effects (see Section 2.4.1), we show that the effect of ICT skills on the sorting into jobs with a high abstract and low routine/manual task content is mainly driven by individuals with intermediate ICT proficiency (Table A-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

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).

[84]Specifically, PIAAC respondents were asked to indicate how often they perform the following activities at work: create or read spreadsheets, use word-processing software, use programming language, and engage in computer-aided real-time discussions. To create a summary index, we follow Kling, Liebman, and Katz (2007) and first calculate the z-score for each of the variables individually, aggregate the z-scores, and normalize by the SD of the aggregate. All calculations are performed for each country individually to account for possible differences in answering behavior.

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

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. This also adds to our discussion of potential age-specific direct broadband effects in Section 2.5.3.

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 2-12 and 2-13, and having high ICT skills appears to be a prerequisite for obtaining these well-paid jobs. Employing back-of-the-envelope calculations, we can provide an idea of how much of the returns to ICT skills can be explained by occupational selection. In regressions of log hourly wages on abstract, routine, and manual task scores, and conditioning on age cohort dummies, female indicator, and country fixed effects, we find that a one SD increase in abstract task content is associated with a 21.3 percent increase in hourly wages, whereas a one SD increase in routine (manual) task content is associated with a 5.2 (2.1) percent increase (decrease) in wages. Multiplying the effect of ICT skills on the occupational task content by the task-wage associations gives: 0.803*21.3 − 0.406*5.2 − 0.343*(-2.1) = 15.7. Based on this simple calculation, occupational selection explains about two-thirds (15.7/23.6=0.665) of the wage increase due to higher ICT skills in the international sample.

Table 2-12: Mechanisms: Occupational Selection (International Evidence)

	Occupational task content			
Second stage	Abstract	Routine	Manual	Computer use
	(1)	(2)	(3)	(4)
ICT skills	0.803***	–0.406**	–0.343**	0.540***
	(0.180)	(0.179)	(0.148)	(0.111)
Age 20–34	–0.925***	0.477***	0.424***	–0.578***
	(0.156)	(0.155)	(0.128)	(0.096)
Age 35–44	–0.565***	0.336***	0.287***	–0.341***
	(0.120)	(0.119)	(0.098)	(0.073)
Age 45–54	–0.286***	0.154***	0.151***	–0.180***
	(0.059)	(0.059)	(0.048)	(0.036)
Female	0.139***	–0.297***	–0.493***	–0.012
	(0.022)	(0.022)	(0.018)	(0.014)
Country fixed effects	X	X	X	X
First stage (Dependent variable: ICT skills)				
Fixed-line diffusion × age 20–34	0.398**	0.398**	0.398**	0.398**
	(0.155)	(0.155)	(0.155)	(0.155)
Fixed-line diffusion × age 35–44	0.840***	0.840***	0.840***	0.841***
	(0.168)	(0.168)	(0.168)	(0.168)
Fixed-line diffusion × age 45–54	0.261	0.261	0.261	0.256
	(0.170)	(0.170)	(0.170)	(0.170)
Cragg-Donald Wald F statistic	27.9	27.9	27.9	28.2
Stock & Yogo critical value	9.1	9.1	9.1	9.1
Individuals	53,132	53,132	53,132	53,110
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 occupation's demand for routine cognitive tasks, and "finger dexterity," measuring an occupation's use of routine motor tasks; and the manual task measure corresponds to the DOT variable measuring an occupation's demand for "eye-hand-foot coordination." The task measures are mapped onto the ISCO occupational classification system (two-digit level) and are normalized to have mean 0 and SD 1 across occupations (Goos, 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 2-13: 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
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 occupation’s demand for routine cognitive tasks, and “finger dexterity,” measuring an occupation’s use of routine motor tasks; and the manual task measure corresponds to the DOT variable measuring an occupation’s demand for “eye-hand-foot coordination.” The task measures are mapped onto the ISCO occupational classification system (two-digit level) and are normalized to have mean 0 and SD 1 across occupations (Goos, 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.

2.8 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 showed 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.[86] The fundamental insight of this paper– that ICT skills can be promoted by providing access to ICT infrastructure –

[86] Alternative employment opportunities will mainly arise in low-paid, manual-intensive occupations that are difficult to automate but require limited formal education (e.g., janitors and cleaners, home health aides,

suggests that the efforts by policy-makers worldwide to expand broadband Internet access may prevent a drifting apart in employment opportunities when advances in ICT change job demands.

and security personnel). See Autor and Dorn (2009) and Goos, Manning, and Salomons (2014) for recent evidence on this "job polarization" hypothesis, and Michaels, Natraj, and Reenen (2014) for an investigation of the role of ICT in polarization of skill demand.

Chapter 3

Online Job Search and Worker Flexibility[§]

3.1 Introduction

"The Internet will change the way that employer-employee matches are made" was predicted by economist David Autor (Autor, 2001) already in 2001. At the same time in Germany, only a negligible share of individuals that had recently found a job reported to have done so online: 0.02 percent. By 2015 this share had increased to roughly 15 percent.

For a search channel gaining importance that quickly, evidence on economic effects is still surprisingly limited and indecisive: While it seems that Online Job Search increased unemployment durations in the early years of the broadband Internet era (Kuhn and Skuterud, 2004), it decreased those durations in later ones (Kuhn and Mansour, 2014). However, there is no effect on unemployment rates (Kroft and Pope, 2014) and, regarding matching, also no effect on wages (Kuhn and Mansour, 2014). Although there is no monetary benefit, individuals who found their new job online tend to be more content with their new work than with their previous (Mang, 2016). Also, individuals tend to switch jobs more often when Internet is available (Stevenson, 2009), at least in the US. While the latter two findings do not seem to go together, it is possible that with Online Job Search as an arguably very cheap search channel, individuals simply continue to look for an even better job.

I add to this literature by documenting worker flexibility in times of Online Job Search along two dimensions: occupation and space, for which I, in large parts, use data from the

[§]I thank Thomas Fackler for help with the data on occupational similarity and Anna Salomons for sharing her data on occupational task content at the ISCO88 level.

German Socio-Economic Panel (SOEP), combined with measures on occupational similarity. My results also document a friction reducing effect of Online Job Search by providing suggestive evidence that it enables workers to look more specifically for jobs in similar occupations.

Flexibility is becoming increasingly important in modern labor markets. With the wide spread fear of computerization leading to job loss (Frey and Osborne, 2017) one would ideally like workers to be able to change their occupation to something less susceptible to these developments. Also, Autor and Dorn (2009) suggest that with age the danger of "getting stuck" in low paying, routine occupations increases. While naturally not everybody can do every job, Gathmann and Schönberg (2010) show that labor market skills are more portable than previously considered.

Furthermore, Marinescu and Rathelot (2016) put forward the idea that jobs could be filled more efficiently when relocating individuals and thus local unemployment could be decreased. While they find little evidence on that to be the case for US labor markets, regional flexibility might nevertheless increase matching outcomes when the "perfect" job is somewhere else and for example drive the results on increased job satisfaction as found in Mang (2016).

The two dimensions of flexibility, flexibility across space and flexibility across occupations, are closely connected: For a lucky individual it may be possible to get into the preferred occupation at the preferred location. However, especially when industries and occupations are clustered, one might have to choose between the one or the other. This is particularly true in a market with frictions, where information on some options stays hidden or is costly to obtain. The possibilities of Online Job Search could act as a real game changer in this context by reducing those frictions. Compared to more traditional search channels it is a) relatively cheap and b) provides the searcher with the universe of job advertisements, combined with the universe of information on the firm itself.

To quantify occupational flexibility, I furthermore present a novel measure for occupational similarity, comparing occupations on the basis of their verbal task descriptions from the International Labour Organisation (ILO) with a machine learning algorithm. To additionally ensure the validity of the measure, I construct another measure in the same way, but this time using different occupational task descriptions from the O*Net database. Results are strikingly similar. As an additional measure of similarity, I look at whether individuals stay in ISCO88 two-digit occupations more, conditional on having changed the four-digit occupation.[1] There is a growing literature on the issue of occupational similarity and the transferability of skills associated with it (e.g. Gathmann and Schönberg, 2010; Nedelkoska, Neffke, and Wiederhold, 2015). I add to this stream by presenting suggestive evidence on a potential channel through which more or less similar occupations can be found, i.e. on whether Online Job Search enables more specific search.

One result of this analysis is that individuals who found their job online show higher regional flexibility on the extensive and the intensive margin: They move significantly more often and also further away. Regarding occupational flexibility, individuals who found their job online do not significantly switch occupations more often. However, I find suggestive evidence that when they do change occupations, they change to *more similar* ones compared to individuals finding their new job elsewhere. This could be interpreted, firstly, as being willing to move regionally in order to not have to move occupation wise. Secondly, especially the results of individuals changing to more similar occupations could be interpreted as evidence that Online Job Search is indeed able to reduce search frictions.

These arguments also fit with the idea of *"Cyber Balkanization"*. This is a highly relevant topic nowadays, especially in the context of news consumption online: The Internet offers the possibility to look for the answers to one's needs much more specifically. While getting information on jobs through a newspaper was either costly or impossible (assuming that some newspapers are regional), online job advertisements have made gathering information easy. I also provide suggestive evidence that this is not only driven by a general information effect of the Internet, but by Online Job Search.

I proceed as follows: Section 3.2 reviews the literature on Online Job Search, Section 3.3 presents the data on Online Job Search and the measures of worker flexibility. Section 3.4 answers the question of which socio-economic groups find work online. Section 3.5 presents the empirical strategy, while Section 3.6 includes the results on worker flexibility. Section 3.7 concludes.

[1]ISCO stands for the International Standard Classification of Occupations. The classification is done by the International Labour Organisation. With ISCO08, ISCO88 already has a successor. However, the ISCO08 category is not available in all of my sample years in the SOEP.

3.2 Literature

Most of the studies on Online Job Search mentioned above provide evidence on US labor markets. For the years 1998 and 2000, Kuhn and Skuterud (2004) find that unemployed Online Job Searchers are negatively selected on observables and even tend to have longer unemployment durations than their Non-Online counterparts. With a different data set, Kuhn and Mansour (2014) find that these early effects might have indeed been driven by a negative selection, for example when individuals lack contacts to help them find a job. These results can partly be explained by another stream of literature. While Internet access is an obvious precondition for Online Job Search, Aguiar, Bils, Charles, and Hurst (2017) show that labor supply of young men is reduced by recreational computer use on the intensive margin.[2] This potentially implies that the leisure potential of the Internet acts as a substitute for the activities such as Online Job Search, and, consequently, decreases labor supply also on the extensive margin. In a similar vein, Section 2.5 of this thesis provides evidence that the cable TV network – often used in the US to roll out broadband infrastructure – did not induce a learning by doing effect in digital skills due to a “distraction effect” of cable TV, whereas the copper wire infrastructure of the telephone network, also used to roll out broadband, did induce such learning. These findings also fit with the results in Kroft and Pope (2014). Using data from *Craigslist*, a huge US web page for different types of ads, they show that the platform could not help in reducing local unemployment rates in the US for the years 2004 to 2006. However, on the housing market – another classic example for a market with search frictions – they find *Craigslist* to lower the vacancy rate.

While, so far, this does not exactly sound like Online Job Search as a game changer as suggested by Autor (2001), effects for more recent years counteract this notion. In their 2014 paper Kuhn and Mansour show that in the period of 2005-2008 Online Job Search had already started to decrease unemployment durations. However, they find no effect on wages, hinting at neither improved nor deteriorated matching on the labor market in the US. Mang (2016), however, suggests that this might simply be the wrong matching outcome and provides evidence that Online Finders are more content with their new work and able to improve their skill usage in the new job.

Kroft and Pope (2014) furthermore suggest that the non-effect they find for unemployment rates might, for example, be driven by increased competition on the labor market due

[2] Aguiar, Bils, Charles, and Hurst (2017) also provides a discussion on how forgone income might be compensated.

to more job changing. This is supported by Stevenson (2009), who shows that having access to the Internet substantially increases the probability of changing jobs, implying increased competition for the unemployed through people coming out of other jobs.

3.3 Data

3.3.1 Online Job Search

The data set I mainly use to study the effect of Online Job Search on worker flexibility is the German Socio-Economic Panel (Wagner, Frick, and Schupp, 2007), from which I employ information from the survey years 2001–2015.[3] The SOEP has been widely used in the economic literature, as indicators for a variety of topics, such as earnings and employment, as well as occupational biographies, are included there. The survey has been conducted since 1984 and today samples about 11,000 households and 30,000 individuals each year. This paper mainly takes advantage of the survey question: "How did you find out about [your new] job?". Since the late 1990s, one of the answering options has been "An advertisement on the Internet". Other potential channels are, for example, personal contacts, newspapers or the employment agency. This question has been previously used in e.g. Mang (2016), to investigate the effect of Online Job Search on matching quality in the sense of reported satisfaction (with e.g. work type) and better use of skills in the new job. By construction, individuals can only report *one* channel, as there can only be one channel over which they, in the end, found their new job. This means that the SOEP comprehensively asks about Online Job *Finding*, rather than Online Job *Search*. While Online Job Search does not necessarily imply Online Job Finding, Online Job Finding implies Online Job Search. I consequently use both terms synonymously.[4]

Through the way the question is asked and the answering channels are presented, what I measure is the effect of *online job advertisements*. Another answering category – "finding over social networks on the Internet" – was only added to the SOEP in 2015. This category is a combination of finding over the Internet and finding over contacts. Only few individ-

[3] However, regarding information on occupations, I partly also employ data from earlier years. See also Section 3.3.3.

[4] However, note that Online Job *Finders*, as a sub-group of Online Job *Searchers*, likely are the ones using the channel most efficiently. Consequently, results for the universe of all Online Job Searchers might differ. Unfortunately, I cannot test this any further with my data. The SOEP asks about Online Job *Search* only for those registered unemployed and in very few years.

uals (68 obs.) reported it, which I excluded from the analysis. Social job networks as e.g. "LinkedIn" or also "Facebook friends" do consequently not pertain to the effect.

Kroft and Pope (2014) present evidence that online job advertisements crowded out those in newspapers in the US. A similar development for Germany is suggested by Figure 3-1. While the number of those reporting to have found their job via a newspaper advertisement is in steady decline, the opposite pertains for those finding their job via an online advertisement. It is possible that in the early years of the sample period an individual found in the newspaper, whereas the exact same one became an Internet finder later on. This might likely be true also due to the nature of change of supply in jobs ads. While, due to the lack of data, I cannot make any claims on the supply side, I account for this in the empirical analysis later on by employing matching and including year fixed effects.

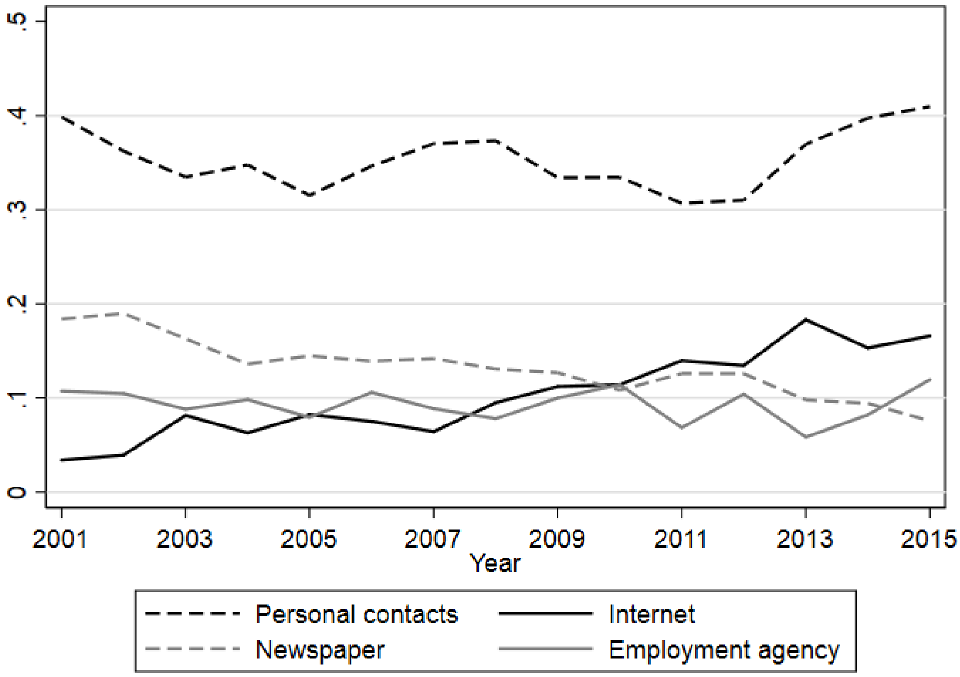
3.3.2 Measures of Regional Flexibility

I measure regional flexibility on the extensive and intensive margin. For this, I use data directly provided in the SOEP since 2001. For the extensive margin, i.e. whether an individual moves, I use a variable that equals unity in case the address of an individual in the SOEP changed from one survey year to the next and is zero if it remained the same. Also, the SOEP provides a variable including the distance between the, potentially, two addresses. The distance is zero when the address stayed the same, i.e. an individual did not move, and has some positive value in the case of a residential move. As I use this as my measure on the intensive margin of regional flexibility, I condition on moving, meaning that there are no zeros. Descriptive statistics for both variables are shown in the upper Panel of Table 3-1.

3.3.3 Measures of Occupational Flexibility

I measure occupational flexibility on the extensive and intensive margin, as well. For the extensive margin, i.e. whether an individual changes her occupation, I construct a dummy for whether there is a change in ISCO88 four-digit occupation between the year before a new job was taken on and the year the new job is reported in the case of job changers. In the case of those previously unemployed or jobless, the information on the last occupation might date several years back, meaning that it might also come from survey years before 2001. For the intensive margin, i.e. to see whether an individual moves to a more distant occupation, I use several different measures. First, I construct a dummy for whether there is a change in ISCO88 two-digit occupation, conditional on having switched the ISCO88 four-digit oc-

Figure 3-1: Development of Job Finding Channels over Time



Notes: Graph shows shares of different job finding methods between the survey years 2001–2015. 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 taking on a new job in the respective year. This includes job changers, those previously unemployed and those previously jobless, without being unemployed. Employment agency includes the German *Arbeitsamt/Agentur fuer Arbeit* as well as the more recent concept of Job Centers (also including social services). Personal contacts also include the separate channels "over family" and "over former colleagues", which were introduced for subsamples in later SOEP years. Shares do not add up to 100 percent because seldom used methods of finding a job are excluded for ease of exposition. *Data sources:* SOEP.

cupation. Because of the way the ISCO classification is constructed, this is a first proxy for similarity. Professionals, for example, are found in ISCO88 major group 2, and therein are divided in e.g. "21 Physical, mathematical and engineering science professionals", "22 Life science and health professionals", ... These two-digit occupations are also referred to as sub-major groups. Also, to give another example, all machine operators and assemblers fall in sub-major group 82. However, this measure is not capable of identifying jobs that are classified somewhere else, but should have a very similar task content. Individuals with secretary duties, for example, could be either classified in ISCO88 four-digit occupation 4115 (Secretaries) or 3431 (Administrative secretaries and related associate professionals). This is, for example, similar for teachers: Four-digit occupation 3310 are Primary education teaching associate professionals while Primary education teaching professionals are classified in 2331.

Table 3-1: Descriptive Statistics for Flexibility Measures

	Mean	**SD**	**Min**	**Max**	**Obs**
Regional Flexibility					
Residential move (dummy)	0.15	0.35	0	1	7559
Distance moved (cond. on move)	69.74	127.61	0.001	761.758	1108
Occupational Flexibility					
Change ISCO88 four-digit (dummy)	0.60	0.49	0	1	7559
Change ISCO88 two-digit (cond. on change)	0.83	0.38	0	1	4550
Similarity Measure (ILO)	0.09	0.11	0	0.99	3433
Similarity Measure (O*Net)	0.13	0.13	0	1	4550

Notes: Descriptive Statistics for measures of regional and occupational flexibility. Distance moved has been trimmed at the 99th percentile in the full SOEP to account for outliers. Similarity measure from ILO and similarity measure from O*Net differ in the number of observations: The similarity measure from ILO is constructed from comparing 364 four-digit occupations, as categories that include the residuum (="nowhere else classified") are not taken into account. Due to the finer level of information in O*Net a comparison of 389 categories is possible. *Data sources:* German Socio-Economic Panel (SOEP), International Labour Organisation, O*Net.

There is a growing literature on the problem of how to better measure occupational similarity and the transferability of skills associated with it. While some measures are constructed on basis of skills used in the respective occupations, others are constructed on basis of the tasks performed. Such data are, for example, available from O*Net (or its predecessor, the Dictionary of Occupational Titles). Poletaev and Robinson (2009), for example, look at the source of human capital specificity and use Euclidean distance to measure occupational distance. Other, more recent, examples are Cortes and Gallipoli (2017) who look at the cost of occupational mobility and Nedelkoska, Neffke, and Wiederhold (2015) who look at skill mismatch after job displacement. Most relevant in this study are likely the findings in Gathmann and Schönberg (2010), showing that individuals move to occupations with similar task requirements and that the distance of moves declines with experience. The question answered in my study adds to their results by presenting a channel through which occupations with more similar task requirements are found.

To account for the "secretary and teacher problem", i.e. that similar occupations are sometimes classified in some other sub-major group, I use two additional, more refined, measures of occupational similarity, new to the literature and based on a machine learning algorithm. For both of them I use verbal job descriptions which are compared with each other by scikit-learn, a machine learning library in Python (Pedregosa et al., 2011). The algorithm, in a slightly modified version, has previously been used in e.g. Fackler (2017) to measure the similarity of patents.[5] The algorithm is based on the term frequency-inverse document frequency matrix (tf-idf matrix). Compared to raw frequencies, i.e. how often words show up, it additionally assigns weights: It automatically gives less weight to words that show up in a large number of occupational descriptions, whereas terms showing in a smaller share of description are given higher weight. Terms that show up in more than 90 percent of descriptions, e.g. articles like "the", are ignored. This yields a measure that is zero for occupations that have nothing in common and one for occupations that have the same task content as far as evident from verbal descriptions. This means the higher the value, the more similar jobs are.[6]

To construct these measures, I use verbal job descriptions from the International Labour Organization (ILO) as well as job descriptions from the O*Net database (v22.0). The occupational descriptions directly from the ILO are at the ISCO88 level already.[7] The data from O*Net is first brought to the ISCO88 level from US O*Net SOC codes with the help of official crosswalks, however providing the more comprehensive descriptions. Reassuringly, the results for measures of occupational similarity from both sources are very similar later on. The least and most similar occupations, as actually showing up as switches in my SOEP sample, are shown in Appendix C. Table C-1 shows the least and most similar occupational switches based on the ILO similarity measure, which are used for the baseline estimations. The least and most similar occupations with respect to the similarity measure generated from O*Net data are shown in Table C-2.

Descriptive Statistics for all occupational flexibility measures, extensive and intensive, are shown in the lower Panel of Table 3-1. The fact that the overall mean of the raw measure for both similarity measures (ILO: Mean 0.04 , SD 0.06; O*NET: Mean 0.07 , SD 0.08) is lower than the one of the actual switches in the SOEP sample, builds further confidence in the measures: The most unlikely switches you might think of are not happening in reality.

[5] As in Fackler (2017) the Natural Language Toolkit (Bird, Klein, and Loper, 2009) is used to prepare the job descriptions for the analysis. The Natural Language Toolkit stems all words with the Porter Stemmer (Porter, 1980), such that ideally all word stems are recognized as such.

[6] For further details on the general procedure, see Fackler, 2017.

[7] Descriptions are taken from `http://www.ilo.org/public/english/bureau/stat/isco/isco88/major.htm`; last accessed March 7, 2018

3.4 Who finds work online?

As Figure 3-1 showed, Online Job Finding is becoming a more common phenomenon. However, it is still not *the* channel for finding a new job. Finding a new job via contacts was and is the most important channel and seems unaffected by the increased possibilities of Online Job Search. In the figure it also looks as though newspaper advertisements are substituted by online advertisements when it comes to the number of job matches made. This raises the question of heterogeneities among the population.

As we know, for example, that the young show a higher technology-affinity, one reason for differences in Online Job Finding that immediately comes to mind is an individual's age.[8] Figure 3-2 shows the share of individuals in the sample, who found a job online, by age. Online Job Search is not linearly decreasing in age, as might have been expected, but follows an inverted u-shaped pattern. While those at the ends of the distribution tend to find their jobs elsewhere to a very large extent, this is less so for those aged roughly 25–34 years, for whom Online Job Finding increases sharply.

However, this is not the only dimension along which Online and Non-Online Finders differ. Descriptive statistics for various socio-demographics are shown separately for Online and Non-Online Finders in Table 3-2. On average, Online Job Finders are younger and (consequently) less likely to be married. However, they are also more highly educated. Furthermore, they more often come from urban regions and are less prevalent in rural regions.[9]

My data set includes three different types of Job Finders: Those changing job, those previously registered unemployed and those re-entering the labor force after a period of joblessness, without having been registered unemployed. The latter, for example, might be parents returning to the labor market. Online Job Finding seems a lot more prevalent for job changers, while for those previously unemployed or jobless other channels of job finding are significantly more important. This is also in line with Stevenson (2009), who finds that the majority of workers using the Internet to gather information about employment are those who are already employed, i.e. that Online Job Search enables easier "On the Job Search", making individuals switch jobs more often in the short run.

[8] Individuals in the sample are limited to those aged 18 to 65 years in the year they took on a new job.

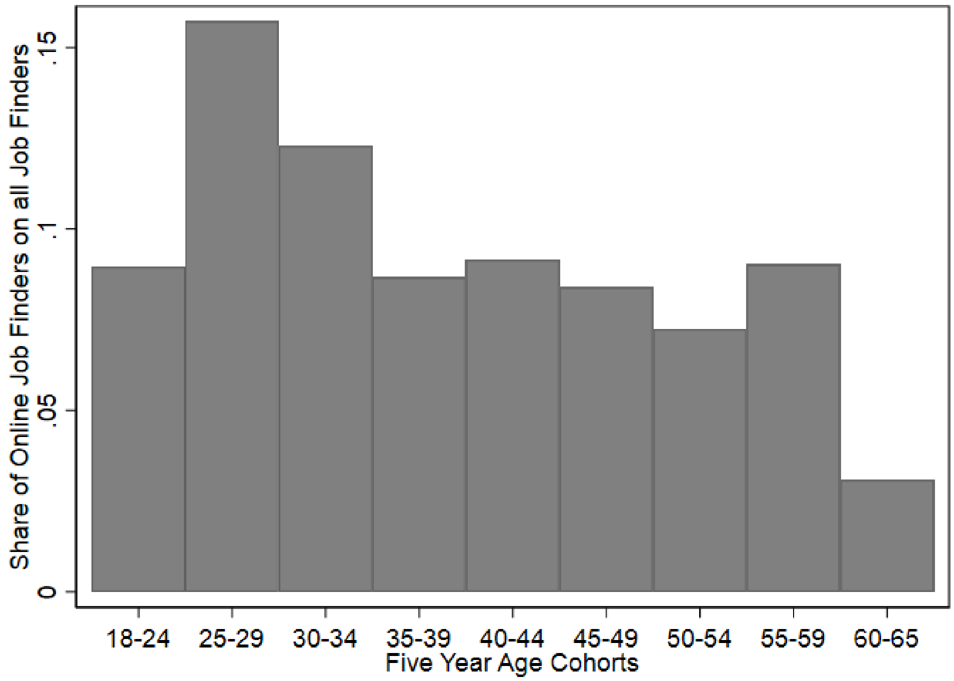
[9] The analysis for regional type refers to the "Regional Planning Unit" (Raumordnungsregion) an individual lived in in the year before finding a new job online, i.e. when making the decision to look for a new job. For details on the "Regional Planning Unit" see Section 3.5.

Table 3-2: Distribution of Job Finders on Basis of Socio-Economic Background

	Online Job Finders	**Other Job Finders**
Age	**35.36**	**37.40**
Female	0.54	0.56
Married	**0.41**	**0.51**
Migration	0.21	0.23
Schooling		
Less than High School	**0.07**	**0.13**
High School	**0.59**	**0.66**
More than High School	**0.34**	**0.20**
Regional type (t-1)		
Urban	**0.53**	**0.43**
Rural to Urban	**0.27**	**0.31**
Rural	**0.20**	**0.26**
Employment Status		
Job Changer	**0.85**	**0.74**
Prev. unemployed	**0.04**	**0.08**
Prev. jobless (w/o unemployed)	**0.10**	**0.18**
Observations	779	6,780

Notes: Descriptive Statistics for Job Finders, pooling the survey years 2001–2015. Numbers are marked in bold for differences at p<0.01 or p<0.05 in t-tests. *Married* is a dummy=1 if individual is married and 0 otherwise. *Migration* is a dummy=1 if individual has a direct or indirect migrational background and 0 otherwise. *Regional type* is measured at the “Regional Planning Unit”-level (Raumordnungsregion) and refers to end of 2015. Sample: German employees aged 16–65 years, who found a job in the respective year. Those might either be job changers, previously unemployed or previously jobless (w/o being registered unemployed). *Data sources:* German Socio-Economic Panel (SOEP), Federal Institute for Building, Urban and Regional Research (BBSR).

Figure 3-2: Online Job Finding by Age



Notes: Graph shows shares of Online Job Finders by five year age cohorts (exceptions are the youngest cohort with seven and oldest cohort with six years) in the survey years 2001–2015. Shares are calculated as number of persons finding a new job via online job advertisements vs. all other methods. *Data sources:* SOEP.

All this indicates that Online Job Finders are a special group. This notion is further supported by Table 3-3, that shows descriptive statistics for differences between Online and Non-Online Finders in different occupational groups (ISCO88, 1-digit). Table 3-3 refers to the previous occupation an individual worked in. Whereas Online Job Finders are significantly more prevalent in "academic" occupations, such as the group of Professionals, they are less prevalent in, for example, elementary occupations. The last line of Table 3-3 shows, that the previous ISCO88 two-digit occupation an individual worked in before taking on the new job was less routine intensive for Online Job Finders.[10] This also fits with the finding of Online Job Finders being more highly educated. I will account for differences in previous occupations by including ISCO88 two-digit fixed effects for the job prior to taking on a new one in the analysis later on.

These statistics also yield potential rationales of the very limited economic effects of Online Job Search, for example on wages, as found in Kuhn and Mansour (2014). As Online

[10]This concept dates back to Autor, Levy, and Murnane (2003). They classify occupations along three dimensions: abstract, manual, and routine task content.

Table 3-3: Distribution of Job Finders across Occupations

	Online Job Finders	Other Job Finders
ISCO88 1-Digit Occupations (prev. job)		
Legislators, Senior Officials and Managers	0.03	0.04
Professionals	**0.24**	**0.14**
Technicians and Associate Professionals	**0.29**	**0.21**
Clerks	0.11	0.12
Service Workers and Shop and Market Sales Workers	0.15	0.18
Skilled Agricultural and Fishery Workers	0.01	0.01
Craft and Related Trades Workers	**0.09**	**0.16**
Plant and Machine Operators and Assemblers	**0.05**	**0.07**
Elementary Occupations	**0.02**	**0.07**
Military	0.00	0.00
Task Measures (prev. job, 2-Digit Occupations)		
Routine Task Intensity (RTI)	**-0.15**	**0.01**
Observations*	779	6,780

Notes: Descriptive Statistics for Job Finders across occupations (ISCO88 1-digit, last occupation before finding the new job; military listed separately), pooling the whole sample. *Routine Task Intensity:* Measure is constructed for 2-digit occupations and as *ln(routine task content) - ln(abstract task content) - ln(manual task content)*, where the routine task measure is the simple, unweighted average of two DOT (Dictionary of Occupational Titles) 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; the abstract task measure is the simple, unweighted 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 manual task measure corresponds to the DOT variable measuring an occupations demand for "eye-hand-foot coordination". * Number of observations 777/6766, respectively, for Routine Task Intensity, as measure is not available for military. Numbers are marked in bold for differences at p<0.01 or p<0.05 in t-tests. Sample: German employees aged 18–65 years, who found a job in the respective year. Those might either be job changers, previously unemployed or previously jobless (w/o being registered unemployed). *Data source:* German Socio-Economic Panel (SOEP), Goos, Manning, and Salomons (2014).

Job Finders are younger than their Non-Online counterparts on average, they are less likely to be "prime agers",[11] whereas we know from the literature that wage premia mostly materialize for this group of workers. As, for example, Jovanovic (1979) points out, workers in their early career are often not perfectly matched with employers, as finding the right "skill-offer skill-demand match" takes some time.[12] This age pattern thus also provides a rationale for the results in Stevenson (2009), that Online Job Searchers tend to switch jobs more often.

3.5 Empirical Strategy

In this setting, simple individual level Ordinary Least Squares or Linear Probability[13] regressions that relate Online Job Finding to different measures of worker flexibility would take on the following form:

$$WorkerFlexibility_{\text{it}} = \beta_0 + \beta_1 OJF_{\text{it}} + \beta_2 \boldsymbol{X}_{\text{it}} + \mu_{\text{t}} + \gamma_{\text{o(prev. job)}} + \theta_{\text{r(t-1)}} + \varepsilon_{\text{it}} \tag{3.1}$$

In this framework $WorkerFlexibility_{\text{it}}$ is one of the outcomes presented in Section 3.4. This is either an indicator for the switch of ISCO88 four-digit occupations, a measure of occupational similarity (a dummy for the change of ISCO88 two-digit occupation and a direct measure of occupational similarity), an indicator for whether an individual moved or not or an indicator for the moving distance. OJF_{it} is an indicator taking on the value 1 when an individual found her job online, and 0 when she found it elsewhere. Regarding individual level covariates in $\boldsymbol{X}_{\text{it}}$, I follow Kuhn and Mansour (2014) and include age, gender, a dummy for whether married or not, an indicator for migration background and indicators for schooling (more than high school diploma, high school diploma, less than high school diploma). As my sample includes job changers as well as those previously unemployed or jobless I also control for these factors.

However, the numbers presented in Table 3-2 suggest that self sorting into Online Job Finding (selection into treatment) is driven by various socio-economic factors. This means results from such simple regressions could still be driven by differences between the two groups. One would ideally like a "matching" control group. I consequently apply exact

[11] Prime agers are defined to be workers between 35 and 54 years of age.

[12] For a more thorough discussion of prime agers as the group with the highest returns to skills see, for example, Hanushek, Schwerdt, Wiederhold, and Woessmann (2015).

[13] Results are very similar when instead computing marginal effects after estimating logit models.

matching via coarsened exact matching, *CEM* (Blackwell, Iacus, King, and Porro, 2009 and Iacus, King, and Porro, 2009), as a means to pre-process the data. CEM provides weights which can easily be used in a following regression analysis to make the two groups comparable on average. After matching on the covariates in $\boldsymbol{X}_{\mathrm{it}}$, I exclude them from the regression. As the matching was only done on dummy indicators for whether unemployed or jobless - a trade off to not lose more observations - I additionally include the unemployment and joblessness durations as covariates in the regressions. Durations are zero for job changers.[14]

To account for potential shocks, such as the financial crisis in the late 2000s and also that someone finding her job via the Internet in 2001 might be substantially different from someone finding over the Internet in 2015, (job finding-)year fixed effects, μ_{t}, are included. Additionally, differences in job finding channels between occupations already became evident in Table 3-3. I thus include occupation fixed effects at the two-digit ISCO88 level (γ_{o}). I here, as done in Table 3-3 as well, use the occupation previous to taking on the new job to only compare individuals coming out of the same occupational sub-major group with each other. The value for the two-digit ISCO88 might date back some years in the case of the previously unemployed or jobless.[15]

Also, one would like to only compare individuals from the same area and not individuals in e.g. very urban regions with those in rural ones. I thus include lagged (i.e. from the year before taking on the new job) regional fixed effects, θ_{r} at the level of the German "Regional Planning Units" (Raumordnungsregionen). "Regional Planning Units" are purely statistical regions, comparable to NUTS2 at the European level. However, in comparison to NUTS2, they are constructed specifically for German statistical needs by the Federal Institute for Building, Urban and Regional Research (BBSR) and allow testaments on inter-regional disparities regarding, for example, the structure of the labor force. They are constructed on basis of county-level commuter linkages. This is especially important when looking at regional flexibility as an outcome.[16]

[14] I construct unemployment and jobless durations from the data. While this results in values measured in whole years, I correct for the month the individual reported to have found a job in.

[15] See also Section 3.3.3.

[16] Further information about the "Regional Planning Units" can be found here: `http://www.bbsr.bund.de/BBSR/DE/Raumbeobachtung/Raumabgrenzungen/Raumordnungsregionen/raumordnungsregionen_node.html`; last accessed February, 2 2018 (in German). The SOEP accounts for territorial changes in the sample period regarding these regions, for example brought about by county reforms, so that no bias can be introduced here.

3.6 Multivariate Evidence on the Relationship between OJS and Flexibility

3.6.1 Occupational Flexibility

I now present results from LPM regressions weighted with weights from CEM on the effect of Online Job Finding on occupational flexibility on the extensive margin, i.e. whether individuals switch occupations more. These are shown in Table 3-4. While I cannot claim causality throughout the analysis, the results are not driven by observable differences in the control and treatment group and also not by selection into these groups, as weights from coarsened exact matching are applied.[17]

I start by including the indicator for Online Job Finding only in Column (1) of Table 3-4. As I matched on dummies for unemployment and joblessness only, to not lose more observations in the exact matching, I additionally control for the respective durations (in years) in Column (2). The duration is zero for job changers and has some positive value for those previously unemployed or jobless, respectively. I include year fixed effects in Column (3) and fixed effects for the last (two digit) occupation in Column (4). Column (5) additionally includes fixed effects for the "Regional Planning Units" in the year previous to taking on a new job. While the sign changes direction multiple times, results always remain very close to zero and are statistically insignificant.

The results are not only statistically insignificant in all specifications, but also negligible in economic terms. The coefficients are very close to zero throughout. This is to say, that Online Job Search does not significantly affect occupational change on the extensive margin, i.e. does not make individuals switch occupations more or less.

Although individuals do not significantly switch occupations more, there is still the possibility that it makes those who do switch, switch to less or more similar occupations. Ex ante, one could think the effect to go in both directions. On the one hand, Online Job Search presents individuals with the universe of jobs, making them hear about unknown possibilities. On the other hand, it enables more specific search. The effect of Online Job Search on occupational similarity, first measured as a dummy for the change of two-digit occupational groups (conditional on having switched four-digit occupations), is shown in

[17] Standard errors are clustered at the individual level to account for the fact that one individual might show up several times throughout the sample period.

Table 3-4: Online Job Finding and Occupational Change

Dependent variable: Occupational Change (ISCO88 4-Digit)					
	(1)	(2)	(3)	(4)	(5)
Online Job Search	0.006	0.006	–0.003	0.001	–0.001
	(0.021)	(0.021)	(0.022)	(0.021)	(0.021)
Unemployment duration		0.062***	0.064***	0.057***	0.064***
		(0.012)	(0.013)	(0.015)	(0.016)
Joblessness duration		0.043***	0.044***	0.039***	0.036***
		(0.006)	(0.007)	(0.006)	(0.006)
Year FE			X	X	X
Occ-2-digit FE (prev. job)				X	X
ROR FE (origin)					X
R squared (adjusted)	–0.00	0.01	0.02	0.09	0.11
Observations	4,584	4,584	4,584	4,584	4,584

Notes: Linear Probability regressions weighted by weights from coarsened exact matching. Sample: German employees aged 18–65 years, who reported to have found a job between 2001-2015. Those might either be job changers, previously unemployed or previously jobless (w/o being registered unemployed). *Online Job Search:* Dummy equals 1 when individual found job online; zero otherwise. *Unemployment duration/joblessness duration:* Time (in years) individual spent being unemployed/being out of the labor force before finding a job; 0 for job changers. *Year Fixed Effects:* Refer to the year individual took on new job. *ROR Fixed Effects (origin):* Refer to the Regional Planning Unit individual lived in in the year before taking on new job. *2-Digit Occupation Fixed Effect (origin):* Refer to the last ISCO88 two-digit occupation individual had before taking on new job (potentially dating some years back in the case of unemployed/jobless). Standard errors, adjusted for clustering at the individual level, in parentheses. Significance levels: * $p<0.10$, ** $p<0.05$, *** $p<0.01$. *Data sources:* German Socio-Economic Panel (SOEP).

Table 3-5. Results are sizable and significant: In my preferred specification in Column (5), Online Job Finding makes individuals less likely to change out of two-digit ISCO88 groups by 8.5 percentage points.

The notion of individuals changing to more similar occupations is further supported by the results in Table 3-6, which presents evidence on occupational similarity as measured by a machine learning algorithm comparing job descriptions from the International Labour Organisation. The significance does not survive the inclusion of too many fixed effects, but still scratches the 10 percent level with p=0.12 in Column (4). However, results at least point in the same direction as before: As the outcome variable increases in the similarity of two occupations, individuals who find jobs online tend to switch to more similar occupations. Coefficients are very similar in magnitude and scratch significance in the first three columns of Table C-3 as well, which shows the results for the O*Net similarity measure.

Table 3-5: Online Job Finding and Occupational Distance - ISCO Groups

Dependent variable: Occupational Change (ISCO88 2-Digit, cond. on 4-Digit Change)					
	(1)	(2)	(3)	(4)	(5)
Online Job Search	–0.097***	–0.096***	–0.106***	–0.088***	–0.085***
	(0.024)	(0.024)	(0.024)	(0.024)	(0.025)
Unemployment duration		0.027***	0.030***	0.010	0.013
		(0.008)	(0.010)	(0.009)	(0.012)
Joblessness duration		0.024***	0.024***	0.017***	0.016***
		(0.004)	(0.004)	(0.004)	(0.004)
Year FE			X	X	X
Occ-2-digit FE (prev. job)				X	X
ROR FE (origin)					X
R squared (adjusted)	0.01	0.02	0.02	0.09	0.10
Observations	2,134	2,134	2,134	2,134	2,134

Notes: Linear Probability regressions weighted by weights from coarsened exact matching. Sample: German employees aged 18–65 years, who reported to have found a job between 2001-2015. Those might either be job changers, previously unemployed or previously jobless (w/o being registered unemployed). *Online Job Search:* Dummy equals 1 when individual found job online; zero otherwise. *Unemployment duration/joblessness duration:* Time (in years) individual spent being unemployed/being out of the labor force before finding a job; 0 for job changers. *Year Fixed Effects:* Refer to the year individual took on new job. *ROR Fixed Effects (origin):* Refer to the Regional Planning Unit individual lived in in the year before taking on new job. *2-Digit Occupation Fixed Effect (origin):* Refer to the last ISCO88 two-digit occupation individual had before taking on new job (potentially dating some years back in the case of unemployed/jobless). Standard errors, adjusted for clustering at the individual level, in parentheses. Significance levels: * p<0.10, ** p<0.05, *** p<0.01. *Data sources:* German Socio-Economic Panel (SOEP).

3.6.2 Regional Flexibility

So far, I have provided suggestive evidence on the effects of Online Job Search on occupational flexibility. I now present results on regional flexibility. For the extensive margin, i.e. whether individuals move more, these are shown in Table 3-7. Regarding the inclusion of additional controls and fixed effects, I proceed the same way I proceeded for occupational flexibility and include them one after the other. The results throughout all specifications in Columns (1)–(5) indicate a positive and significant effect of Online Job Search on moving. Individuals who find a new job online are more than 6 percentage points more likely to move.

Table 3-8 shows the results from the intensive margin, i.e. how far people move, conditional on moving. This leaves only roughly 400 observations in the matched sample, making the specification with year, two-digit occupation and Regional Planning Unit-fixed effects extremely demanding.[18] While the effect is positive in the preferred specification in Column

[18]There are 96 Regional Planning Units.

Table 3-6: Online Job Finding and Occupational Distance - ILO Similarity Measure

Dependent variable: Occupational Similarity					
	(1)	(2)	(3)	(4)	(5)
Online Job Search	0.014*	0.015*	0.016*	0.012	0.009
	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)
Unemployment duration		–0.008***	–0.010***	–0.005**	–0.000
		(0.002)	(0.003)	(0.002)	(0.003)
Joblessness duration		–0.007***	–0.007***	–0.004***	–0.004***
		(0.001)	(0.001)	(0.001)	(0.002)
Year FE		X	X	X	X
Year × Age Cohort FE			X	X	X
Occ-2-digit FE (prev. job)				X	X
ROR FE (origin)					X
R squared (adjusted)	0.00	0.01	0.02	0.16	0.20
Observations	1,337	1,337	1,337	1,337	1,337

Notes: Least Squares regressions weighted by weights from coarsened exact matching. Sample: German employees aged 18–65 years, who reported to have found a job between 2001-2015. Those might either be job changers, previously unemployed or previously jobless (w/o being registered unemployed). *Online Job Search:* Dummy equals 1 when individual found job online; zero otherwise. *Unemployment duration/joblessness duration:* Time (in years) individual spent being unemployed/being out of the labor force before finding a job; 0 for job changers. *Year Fixed Effects:* Refer to the year individual took on new job. *ROR Fixed Effects (origin):* Refer to the Regional Planning Unit individual lived in in the year before taking on new job. *2-Digit Occupation Fixed Effect (origin):* Refer to the last ISCO88 two-digit occupation individual had before taking on new job (potentially dating some years back in the case of unemployed/jobless). Standard errors, adjusted for clustering at the individual level, in parentheses. Significance levels: * $p<0.10$, ** $p<0.05$, *** $p<0.01$. *Data sources:* German Socio-Economic Panel (SOEP), International Labour Organisation (ILO).

(5), the effect of individuals who found their job online, moving around 30 km further, is insignificant. However, once I loosen the fixed effects to state instead of Regional Planning Unit-fixed effects, results remain significant throughout the specifications. These are shown in Table C-4 in Appendix C. Online Job Search consequently seems to make individuals move further and more.

This is especially interesting in light of the results in Falck, Lameli, and Ruhose (2016) who show that individuals moving to a culturally different location need to be compensated. The finding that individuals move to more similar occupations but to more distant places in geographic terms, connects the findings in Falck, Lameli, and Ruhose (2016) to the findings in Mang (2016): Being able to stay in one's "occupational comfort zone", with higher job satisfaction (and potentially higher wages), works as such a compensation.

Table 3-7: Online Job Finding and Regional Change

Dependent variable: Residential Move					
	(1)	(2)	(3)	(4)	(5)
Online Job Search	0.052***	0.053***	0.060***	0.056***	0.064***
	(0.018)	(0.018)	(0.018)	(0.018)	(0.018)
Unemployment duration		–0.001	–0.002	0.003	0.003
		(0.017)	(0.016)	(0.016)	(0.016)
Joblessness duration		–0.011**	–0.012***	–0.010**	–0.008*
		(0.004)	(0.004)	(0.004)	(0.005)
Year FE			X	X	X
Occ-2-digit FE (prev. job)				X	X
ROR FE (origin)					X
R squared (adjusted)	0.00	0.00	0.01	0.02	0.04
Observations	4,584	4,584	4,584	4,584	4,584

Notes: Linear Probability regressions weighted by weights from coarsened exact matching. Sample: German employees aged 18–65 years, who reported to have found a job between 2001-2015. Those might either be job changers, previously unemployed or previously jobless (w/o being registered unemployed). *Online Job Search:* Dummy equals 1 when individual found job online; zero otherwise. *Unemployment duration/joblessness duration:* Time (in years) individual spent being unemployed/being out of the labor force before finding a job; 0 for job changers. *Year Fixed Effects:* Refer to the year individual took on new job. *ROR Fixed Effects (origin):* Refer to the Regional Planning Unit individual lived in in the year before taking on new job. *2-Digit Occupation Fixed Effect (origin):* Refer to the last ISCO88 two-digit occupation individual had before taking on new job (potentially dating some years back in the case of unemployed/jobless). Standard errors, adjusted for clustering at the individual level, in parentheses. Significance levels: * p<0.10, ** p<0.05, *** p<0.01. *Data sources:* German Socio-Economic Panel (SOEP).

3.6.3 Robustness

While the last paragraphs presented suggestive evidence that individuals who found online move more and likely further and do not leave their occupational "comfort zone", unobserved factors might be driving these results. For example, one might be worried that what I find is not an effect of Online Job Search, but a general information effect of the Internet, especially when it comes to moving, as also the new flat or information about the new region might be found online. The same is true, however, for information on the new firm. I consequently include Internet access in the year before taking on a new job, i.e. when looking for it, in the regressions in Table 3-9. The information on Internet availability in households is only available for very few years,[19] drastically reducing the sample size. Baseline estimations for the newly matched samples for residential move, two-digit occupation change (conditional on four-digit change) and both distance measures for occupational similarity are shown

[19]It is available only in 2005, 2007, 2011, 2013, 2014 and 2015. However, as I include availability in the year before finding a new job and my sample reaches until 2015 only, I do not utilize the information on Internet availability in 2015.

Table 3-8: Online Job Finding and Regional Distance

Dependent variable: Distance of Res. Move (in km)					
	(1)	(2)	(3)	(4)	(5)
Online Job Search	51.776***	52.011***	63.411***	51.826**	27.252
	(19.435)	(19.439)	(20.351)	(20.699)	(23.008)
Unemployment duration		12.673	–31.543	67.215	193.511
		(199.254)	(206.193)	(167.614)	(226.490)
Joblessness duration		–8.981	–11.817	–27.393**	–54.479**
		(15.145)	(16.730)	(13.041)	(23.248)
Year FE			X	X	X
Occ-2-digit FE (prev. job)				X	X
ROR FE (origin)					X
R squared (adjusted)	0.02	0.02	0.04	0.08	0.19
Observations	416	416	416	416	416

Notes: Least Squares regressions weighted by weights from coarsened exact matching. Sample: German employees aged 18–65 years, who reported to have found a job between 2001-2015. Those might either be job changers, previously unemployed or previously jobless (w/o being registered unemployed). *Online Job Search:* Dummy equals 1 when individual found job online; zero otherwise. *Unemployment duration/joblessness duration:* Time (in years) individual spent being unemployed/being out of the labor force before finding a job; 0 for job changers. *Year Fixed Effects:* Refer to the year individual took on new job. *ROR Fixed Effects (origin):* Refer to the Regional Planning Unit individual lived in in the year before taking on new job. *2-Digit Occupation Fixed Effect (origin):* Refer to the last ISCO88 two-digit occupation individual had before taking on new job (potentially dating some years back in the case of unemployed/jobless). Standard errors, adjusted for clustering at the individual level, in parentheses. Significance levels: * $p<0.10$, ** $p<0.05$, *** $p<0.01$. *Data sources:* German Socio-Economic Panel (SOEP).

in Columns (1), (3), (5) and (7), respectively. The limited sample sizes lead to a loss of significance in most specifications. However, the size of the coefficients remains of very similar magnitude when including a dummy for Internet in the household in Columns (2), (4), (6) and (8), indicating an effect of Online Job Search itself over a pure Internet information effect.

Table 3-9: Control for Internet Availability in Household

Dependent variable:	Occup. Change (2-Digit)		Occup. Simil. (ILO)		Occup. Simil. (O*Net)		Residential Move	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Online Job Search	–0.032	–0.032	0.023	0.023	0.010	0.010	0.059*	0.059*
	(0.051)	(0.051)	(0.019)	(0.019)	(0.018)	(0.018)	(0.035)	(0.035)
Unemployment duration	–0.402	–0.428	0.100	0.109	0.034	0.032	0.170**	0.174**
	(0.504)	(0.498)	(0.118)	(0.119)	(0.115)	(0.122)	(0.076)	(0.076)
Joblessness duration	0.006	0.006	–0.003	–0.003	0.000	0.000	–0.016*	–0.016*
	(0.009)	(0.009)	(0.003)	(0.003)	(0.005)	(0.005)	(0.009)	(0.009)
Internet in HH		0.045		–0.009		0.003		–0.017
		(0.085)		(0.026)		(0.036)		(0.060)
Year FE	X	X	X	X	X	X	X	X
Occ-2-digit FE (prev. job)	X	X	X	X	X	X	X	X
ROR FE (origin)	X	X	X	X	X	X	X	X
R squared (adjusted)	0.08	0.08	0.16	0.16	0.09	0.09	0.13	0.12
Observations	435	435	248	248	435	435	978	978

Notes: Least Squares regressions weighted by weights from coarsened exact matching, done separately for the residential move and all occupational similarity samples. Sample: German employees aged 18–65 years, who reported to have found a job between 2001-2015. Those might either be job changers, previously unemployed or previously jobless (w/o being registered unemployed). *Online Job Search:* Dummy equals 1 when individual found job online; zero otherwise. *Unemployment duration/joblessness duration:* Time (in years) individual spent being unemployed/being out of the labor force before finding a job; 0 for job changers. *Internet:* Dummy for whether household had Internet in the year before taking on new job. *Year Fixed Effects:* Refer to the year individual took on new job. *ROR Fixed Effects (origin):* Refer to the Regional Planning Unit individual lived in in the year before taking on new job. *2-Digit Occupation Fixed Effect (origin):* Refer to the last ISCO88 two-digit Occupation individual had before taking on new job (potentially dating some years back in the case of unemployed/jobless). Standard errors, adjusted for clustering at the individual level, in parentheses. Significance levels: * $p<0.10$, ** $p<0.05$, *** $p<0.01$. *Data sources:* German Socio-Economic Panel (SOEP), International Labour Organisation (ILO), O*Net.

3.7 Conclusion

This study analyzes the effect of Online Job Search on worker flexibility. It shows that Online Job Search is a useful tool in reducing search frictions, by enabling more directed and specific search from an occupational and geographical viewpoint: Individuals, when switching jobs, tend to switch to more similar occupations when finding their new job online, while they also seem to switch to more geographically distant jobs. While this is also suggestive evidence that Online Job Finding helps in making labor markets less local, it speaks for “occupational comfort zones” where individuals are even willing to move to stay in a similar occupation.

The results, however, are not driven by a pure information effect of the Internet, for example by enabling more ex ante information on a respective region (e.g. housing market) or job, as robustness checks show. Results are also not driven by sorting into treatment, as coarsened exact matching (CEM) is applied.

The findings on occupational flexibility are also relevant in practice. Janssen and Mohrenweiser (2018) provide an example where the introduction of a new technology leads to the task specific human capital of the incumbent workers becoming redundant and to a crowding out of those workers once specifically and newly trained workers enter the market. They present results on those incumbent workers changing out of their occupation as a consequence. While this development took place before the period of Online Job Search, this shows that individuals having to move out of occupations is something happening in reality.

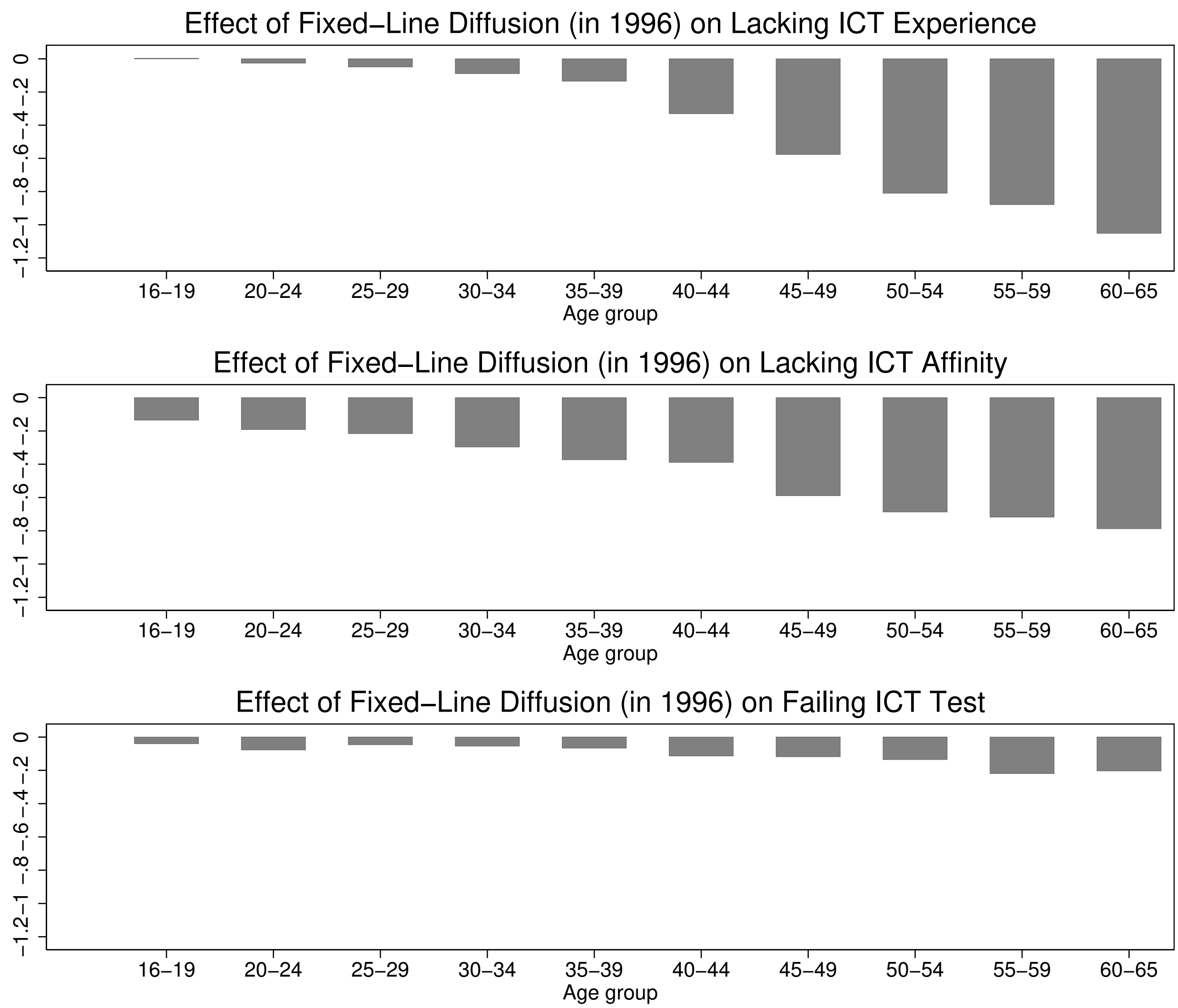
Also increased regional mobility has implications in practice, as underlined by another recent piece of literature. Huttunen, Møen, and Salvanes (2018) show that displaced workers move more and are partly even able to realize a long-term earnings increase. Online Job Search might act as an enabler here. However, the SOEP is not the right data set to study displaced workers specifically in the context of Online Jobs Search due to too few observations, meaning that I cannot directly test this notion. Nevertheless, this potentially provides a valuable starting point for future research.

The fact that, regarding occupations, Online Job Search does not seem to work flexibility increasing, is in line with a “cyber balkanization”, i.e. individuals rather seizing the chance of finding a more related job than exploring something new. These results consequently also provide a rationale for the findings in Mang (2016), which show that jobs found online lead to better matched individuals, in terms of satisfaction with and skill use on the job. Especially the finding for higher happiness with the work type fit with this notion. My findings also relate to the results in Falck, Lameli, and Ruhose (2016), who show that individuals need to be compensated for moving to a different location. This might happen by them being allowed to stay in their "occupational comfort zone" (with potentially higher wages) and find their happiness there.

Appendix A

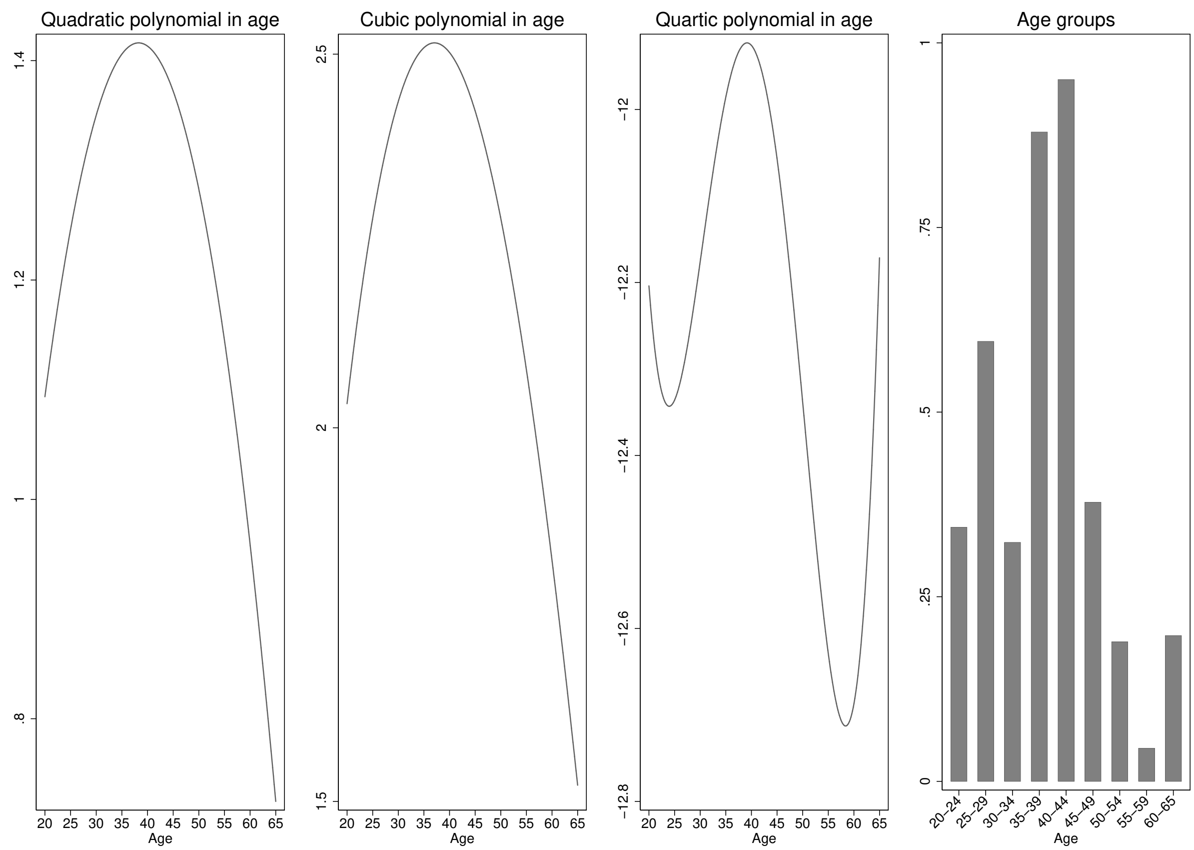
Returns to ICT Skills: Additional Figures and Tables

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



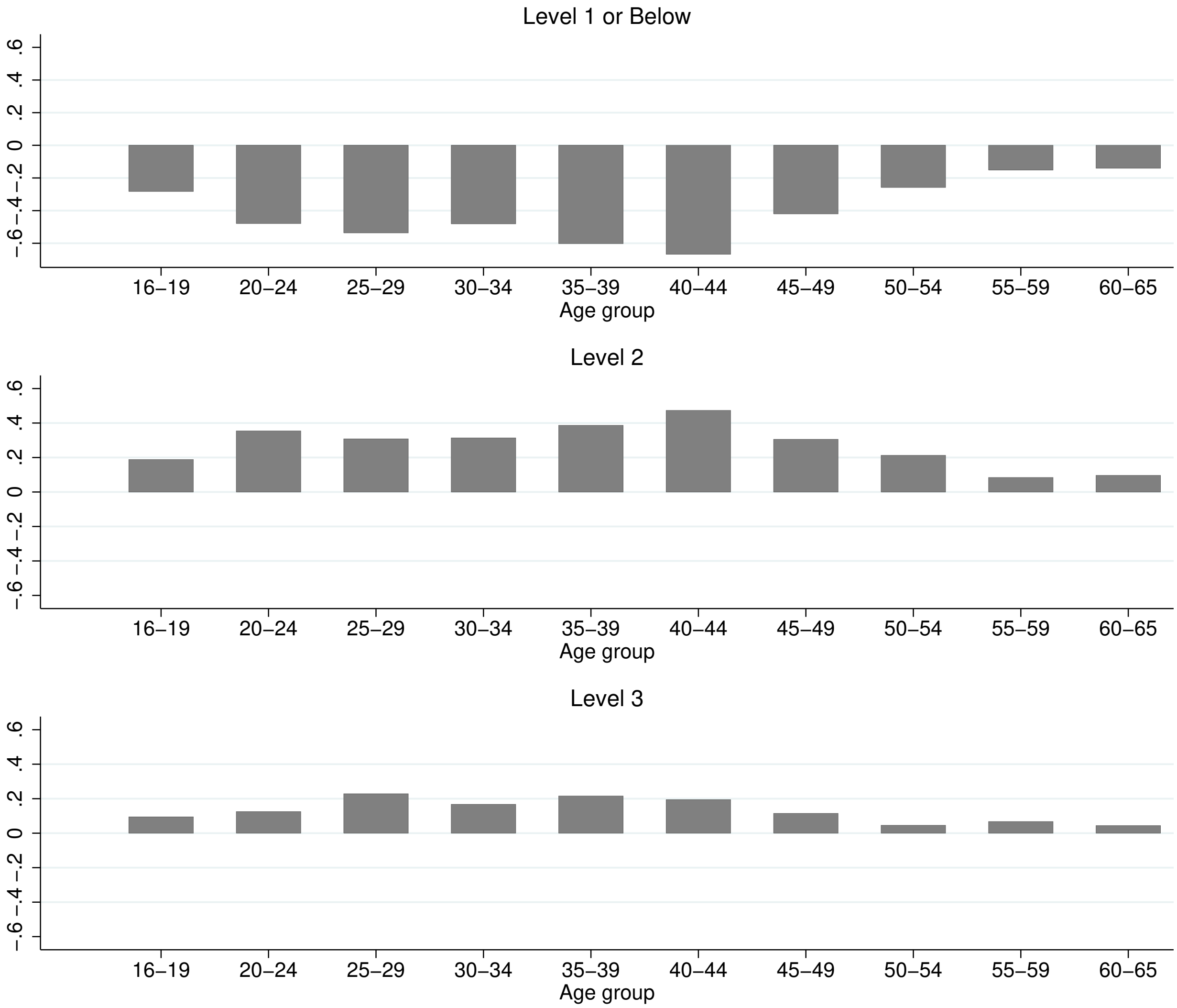
Notes: Coefficient estimates on fixed-line voice-telephony diffusion (in 1996) for indicated age groups in a regression of ICT illiteracy on fixed-line diffusion, by reason for ICT illiteracy. ICT skills can be missing in PIAAC due to lack of computer experience reported by the respondent (Panel A), 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



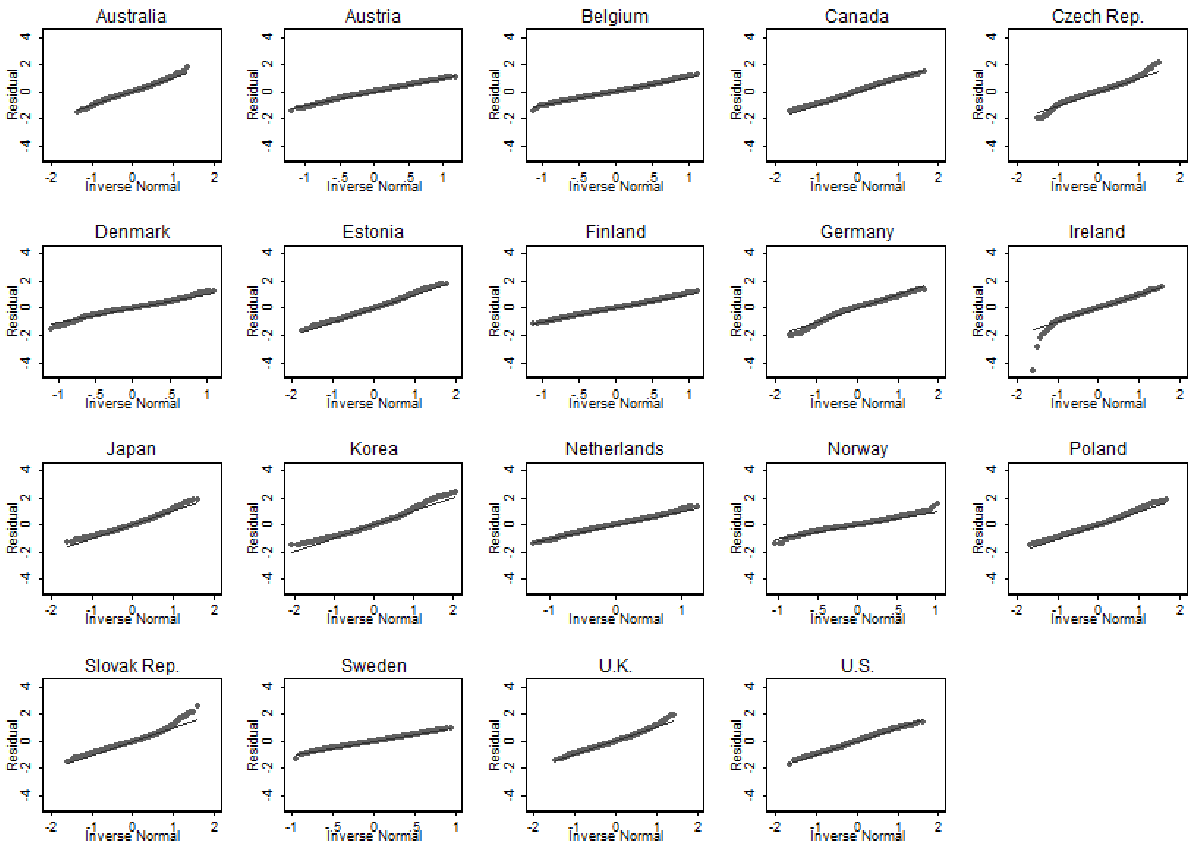
Notes: Coefficient estimates on fixed-line diffusion (in 1996) interacted with various functional forms of age (indicated in the panel heading) in a regression of ICT skills (standardized to SD 1 across countries) on fixed-line-diffusion-age interactions, respective age variables, gender, and country 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



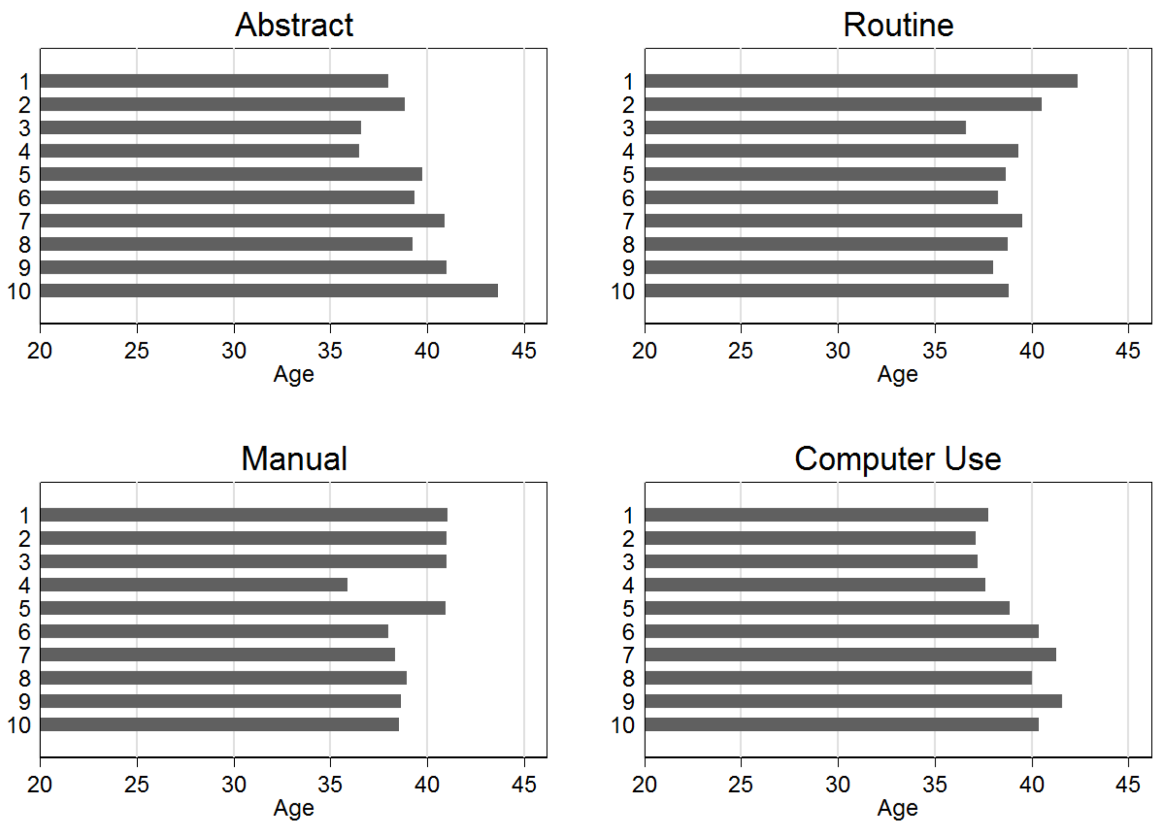
Notes: Coefficient estimates on fixed-line voice-telephony diffusion (in 1996) for indicated age groups in a regression of ICT proficiency on fixed-line diffusion. ICT proficiency is a binary variable indicating whether a person has the ICT proficiency level mentioned in the panel header, and 0 otherwise: 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 × age 20–34	0.505***	0.384**
	(0.155)	(0.155)
Fixed-line diffusion × age 35–44	0.920***	0.839***
	(0.169)	(0.168)
Fixed-line diffusion × age 45–54	0.288*	0.253
	(0.171)	(0.170)
Age 20–34	0.841***	0.848***
	(0.017)	(0.017)
Age 35–44	0.643***	0.646***
	(0.017)	(0.017)
Age 45–54	0.297***	0.301***
	(0.018)	(0.018)
Female	–0.120***	–0.112***
	(0.010)	(0.010)
Country fixed effects		X
Individuals	53,879	53,879

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

Table A-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***	0.351***	–0.157***	–0.224***
	(0.011)	(0.024)	(0.025)	(0.021)
× level 1 or below	–0.013	–0.073***	0.088***	0.021
	(0.013)	(0.027)	(0.028)	(0.023)
× level 3	–0.086***	–0.234***	0.160***	0.199***
	(0.024)	(0.051)	(0.053)	(0.040)
Level 1 or below	–0.032	–0.175***	0.163**	0.155***
	(0.026)	(0.060)	(0.064)	(0.056)
Level 3	0.117*	0.258*	–0.160	–0.246**
	(0.062)	(0.133)	(0.133)	(0.097)
Individual Characteristics	X	X	X	X
Country fixed effects	X	X	X	X
Interactions with ICT-proficiency level	X	X	X	X
R squared	0.46	0.13	0.05	0.13
Individuals	53,879	53,132	53,132	53,132

Notes: Least squares regressions weighted by sampling weights (giving same weight to each country). Sample: employees aged 20–65 years, no first-generation immigrants (in Columns (2)–(4), individuals who did not provide information on their occupation are excluded). Dependent variable is the logarithm of gross hourly wage (in PPP-USD) in Column (1) and task measures taken from Goos, 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***	–0.369***	–0.592***	–0.517***
	(0.102)	(0.114)	(0.126)	(0.153)
Unemployment rate in 1999	–2.152	–2.582**	–0.986	1.073
	(1.376)	(1.261)	(3.846)	(5.448)
Population share 65+ in 1999	–0.837	–0.886	–5.126*	–6.941**
	(1.312)	(1.253)	(2.650)	(2.602)
Experience		–0.004		–0.004
		(0.007)		(0.025)
Experience^2 (/100)		–0.052***		–0.070
		(0.016)		(0.053)
Female		–0.149***		–0.292*
		(0.046)		(0.145)
Individuals	1,849	1,849	160	160
Municipalities	204	204	18	18

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

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

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

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

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

Table 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**	0.300**	0.311**	0.302**	0.306**	0.521**	0.550**	0.518**	0.585**	0.619**
	(0.151)	(0.152)	(0.150)	(0.151)	(0.153)	(0.213)	(0.223)	(0.209)	(0.231)	(0.244)
Age		0.064***			0.068***		–0.045			–0.047
		(0.015)			(0.015)		(0.076)			(0.084)
Age^2 (/100)		–0.061***			–0.062***		0.064			0.067
		(0.019)			(0.019)		(0.091)			(0.099)
Full-time			0.146***		0.196***			0.165		0.152
			(0.040)		(0.039)			(0.182)		(0.233)
Native				–0.024	–0.005				0.469**	0.500**
				(0.033)	(0.032)				(0.239)	(0.225)
Individual characteristics	X	X	X	X	X	X	X	X	X	X
Municipality characteristics	X	X	X	X	X	X	X	X	X	X
First stage (Dependent variable: ICT skills)										
Threshold	–0.369***	–0.364***	–0.370***	–0.369***	–0.365***	–0.517***	–0.491***	–0.513***	–0.474***	–0.443***
	(0.114)	(0.116)	(0.114)	(0.114)	(0.116)	(0.153)	(0.134)	(0.153)	(0.149)	(0.131)
Kleibergen-Paap F statistic	10.5	9.9	10.5	10.5	9.9	11.5	13.5	11.2	10.2	11.3
Individuals	1,849	1,849	1,849	1,849	1,849	160	160	160	160	160
Municipalities	204	204	204	204	204	18	18	18	18	18

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

Appendix B

Returns to ICT Skills: Measurment Error

Like in any performance assessment, ICT skills in PIAAC are likely an error-ridden measure of a persons 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:

$$\log w = \beta\lambda ICT + \varepsilon, \tag{B.1}$$

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:

$$\hat{\beta} = \beta\left(1 - \frac{Var(u)}{Var(ICT)}\right), \tag{B.2}$$

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, $Var(ICT \mid X) < Var(ICT)$, but $Var(u)$ remains the same (see also Griliches and Hausman (1986)). To calculate $Var(ICT \mid X)$, 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

[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 Cronbachs 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 (2017) use Cronbachs α to correct for measurement error in tested teacher subject knowledge. While Cronbachs 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 Statas 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 Cronbachs α is very similar to the reliability ratios reported by the OECD.

measurement-error-corrected estimate of the effect of ICT skills on wages. For our baseline OLS coefficient of 0.122, this implies a corrected effect of 0.203.

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

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

[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.

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

Table B-1: Measurment Error

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

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

Appendix C

Online Job Search and Worker Flexibility: Additional Figures and Tables

Table C-1: Least and Most Similar Occupations as showing in the SOEP Sample (ILO Similarity Measure)

Similarity	(ILO)			
Lowest				
0	4190	Other office clerks	8322	Car, taxi and van drivers
0	4190	Other office clerks	8322	Car, taxi and van drivers
0	4190	Other office clerks	9161	Garbage collectors
0	5122	Cooks	4215	Debt-collectors and related workers
0	5122	Cooks	4223	Telephone switchboard operators
0	5122	Cooks	7143	Building structure cleaners
0	5122	Cooks	7143	Building structure cleaners
0	5122	Cooks	7422	Cabinet-makers and related workers
0	5122	Cooks	8163	Incinerator, water-treatment and related plant operators
0	5122	Cooks	8290	Other machine operators and assemblers
0	5122	Cooks	8324	Heavy truck and lorry drivers
0	5122	Cooks	9142	Vehicle, window and related cleaners
0	5123	Waiters, waitresses and bartenders	4223	Telephone switchboard operators
0	5123	Waiters, waitresses and bartenders	7233	Agricultural- or industrial-machinery mechanics and fitters
0	5123	Waiters, waitresses and bartenders	8211	Machine-tool operators
0	7223	Machine-tool setters and setter-operators	7311	Precision-instrument makers and repairers
0	7233	Agricultural- or industrial-machinery mechanics and fitters	8232	Plastic-products machine operators
0	7245	Electrical line installers, repairers and cable jointers	3412	Insurance representatives
0	7311	Precision-instrument makers and repairers	3222	Sanitarians
0	7311	Precision-instrument makers and repairers	5123	Waiters, waitresses and bartenders
0	8232	Plastic-products machine operators	4133	Transport clerks
0	8322	Car, taxi and van drivers	4221	Travel agency and related clerks
0	8322	Car, taxi and van drivers	7245	Electrical line installers, repairers and cable jointers
0	8322	Car, taxi and van drivers	7311	Precision-instrument makers and repairers
0	8324	Heavy truck and lorry drivers	4221	Travel agency and related clerks
0	9161	Garbage collectors	9313	Building construction labourers
Highest				
0.6025115	3115	Mechanical engineering technicians	3113	Electrical engineering technicians
0.6121159	2143	Electrical engineers	2144	Electronics and telecommunications engineers
0.6277427	3111	Chemical and physical science technicians	3212	Agronomy and forestry technicians
0.7002076	8271	Meat- and fish-processing-machine operators	7411	Butchers, fishmongers and related food preparers
0.8475955	1314	General managers in wholesale and retail trade	1315	General managers of restaurants and hotels
0.9858682	2446	Social work professionals	3460	Social work associate professionals

Notes: Most distant (similarity value 0) and closest (similarity value >0.6) Occupational switches as showing in the sample. Several of the switches show more often (i.e. several individuals switched from and to the respective occupation) and in both directions. Excluded for the ease of exposition. *Data sources:* German Socio-Economic Panel (SOEP), International Labor Organisation (ILO).

Table C-2: Least and Most Similar Occupations as showing in the SOEP Sample (O*Net Similarity Measure)

Similarity	**(O*Net)**			
Lowest				
0	3449	Customs, tax and related government associate professionals n.e.c.	7113	Stone splitters, cutters and carvers
0	3480	Religious associate professionals	9141	Building caretakers
0	3442	Government tax and excise officials	4212	Tellers and other counter clerks
0	8141	Wood-processing-plant operators	5121	Housekeepers and related workers
0	8275	Grain- and spice-milling-machine operators	7437	Upholsterers and related workers
0	2422	Judges	3480	Religious associate professionals
0	2429	Legal professionals not elsewhere classified	7442	Pelt dressers, tanners and fellmongers
0	7437	Upholsterers and related workers	9313	Building construction laborers
0	5122	Cooks	7433	Tailors, dressmakers and hatters
0	2443	Philosophers, historians and political scientists	3449	Customs, tax and related government associate professionals
Highest				
0.827	4115	Secretaries	3431	Administrative secretaries and related associate professionals
0.889	3113	Electrical engineering technicians	3114	Electronics and telecommunications engineering technicians
0.890	1311	Managers of small enterprises in agriculture, hunting, forestry and fishing	6112	Tree and shrub crop growers
0.892	3115	Mechanical engineering technicians	3152	Safety, health and quality inspectors
0.906	2419	Business professionals not elsewhere classified	3429	Business services agents and trade brokers n.e.c.
0.944	3229	Health associate professionals (except nursing) n.e.c.	3226	Physiotherapists and related associate professionals
0.992	7223	Machine-tool setters and setter-operators	8211	Machine-tool operators
1	8121	Ore and metal furnace operators	8122	Metal melters, casters and rolling-mill operators

Notes: Most distant (similarity value 0) and closest (similarity value >0.8) Occupational switches as showing in the sample. Several of the switches show more often (i.e. several individuals switched from and to the respective occupation) and in both directions. Excluded for the ease of exposition.
Data sources: German Socio-Economic Panel (SOEP), O*Net.

Table C-3: Online Job Finding and Occupational Distance - O*Net Similarity Measure

Dependent variable: Occupational Similarity	(1)	(2)	(3)	(4)	(5)
Online Job Search	0.014	0.014	0.015	0.012	0.009
	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)
Unemployment duration		–0.001	–0.003	0.002	0.006
		(0.006)	(0.005)	(0.005)	(0.005)
Joblessness duration		–0.004	–0.004	–0.002	–0.003
		(0.003)	(0.003)	(0.002)	(0.003)
Year FE		X	X	X	X
Occ-2-digit FE (prev. job)				X	X
ROR FE (origin)					X
R squared (adjusted)	0.00	0.00	0.01	0.08	0.11
Observations	2,134	2,134	2,134	2,134	2,134

Notes: Least Squares regressions weighted by weights from Coarsened Exact Matching. Sample: German employees aged 18–65 years, who found a job. Those might either be job changers, previously unemployed or previously jobless (w/o being registered unemployed). *Online Job Search:* Dummy equals 1 when individual found job online; zero otherwise. *Unemployment duration/joblessness duration:* Time (in years) individual spent being unemployed/being out of the labor force before finding a job; 0 for job changers. *Year Fixed Effects:* Refer to the year individual took on new job. *ROR Fixed Effects (origin):* Refer to the Regional Planning Unit individual lived in in the year before taking on new job. *2-Digit Occupation Fixed Effect (origin):* Refer to the last ISCO88 2-Digit Occupation individual had before taking on new job (potentially dating some years back in the case of Unemployed/jobless). Standard errors, adjusted for clustering at the individual level, in parentheses. Significance levels: * p<0.10, ** p<0.05, *** p<0.01. *Data sources:* German Socio-Economic Panel (SOEP), O*Net.

Table C-4: Online Job Finding and Regional Distance

Dependent variable: Distance of Res. Move (in km)					
	(1)	(2)	(3)	(4)	(5)
Online Job Search	51.776***	52.011***	63.411***	51.826**	48.851**
	(19.435)	(19.439)	(20.351)	(20.699)	(20.824)
Unemployment duration		12.673	–31.543	67.215	17.122
		(199.254)	(206.193)	(167.614)	(157.223)
Joblessness duration		–8.981	–11.817	–27.393**	–28.006**
		(15.145)	(16.730)	(13.041)	(13.672)
Year FE			X	X	X
Occ-2-digit FE (prev. job)				X	X
State FE (origin)					X
R squared (adjusted)	0.02	0.02	0.04	0.08	0.13
Observations	416	416	416	416	416

Notes: Least Squares regressions weighted by weights from Coarsened Exact Matching. Sample: German employees aged 18–65 years, who found a job. Those might either be job changers, previously unemployed or previously jobless (w/o being registered unemployed). *Online Job Search:* Dummy equals 1 when individual found job online; zero otherwise. *Unemployment duration/joblessness duration:* Time (in years) individual spent being unemployed/being out of the labor force before finding a job; 0 for job changers. *Year Fixed Effects:* Refer to the year individual took on new job. *ROR Fixed Effects (origin):* Refer to the Regional Planning Unit individual lived in in the year before taking on new job. *2-Digit Occupation Fixed Effect (origin):* Refer to the last ISCO88 2-Digit Occupation individual had before taking on new job (potentially dating some years back in the case of Unemployed/jobless). Standard errors, adjusted for clustering at the individual level, in parentheses. Significance levels: * p<0.10, ** p<0.05, *** p<0.01. *Data sources:* German Socio-Economic Panel (SOEP).

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