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Broadband Internet and Labour Market Dynamism*

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Abstract

We investigate the response of posted job vacancies to increased broadband connectivity with a specific focus on their requirements for digital and cognitive skills, and distinguishing the effects between digital and non-digital occupations. We utilise a large dataset of online job advertisements, which encompasses approximately 55,000 observations between 2013 and 2019. Broadband shocks unambiguously increase vacancy postings, but do not significantly impact their skill composition. By contrast, fast broadband shocks induce heterogeneous responses, where vacancies posted for non-digital occupations increase their digital/cognitive skill contents, whereas we obtain opposite results for digital occupations.

Keywords: Broadband, Online Job Advertisements, digital skills, cognitive skills
JEL codes: J24, J63, L96

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1 Introduction

Internet access has been a key factor driving the Information and Communications Technology (ICT) revolution, which has reshaped the world economy. Since the onset of this process, the ICT creative destruction potential has raised concerns for its labour market implications (see Acemoglu (2002)). According to Autor (2001), broadband access can affect labour market outcomes through several mechanisms. First, customers' internet access can strengthen goods market integration: most productive firms can target larger geographical markets at the expense of less productive local firms. Second, broadband internet access can be viewed as a general-purpose technology that supports the development of Information and Communication Technologies (ICT), a well-known source of skill-biased technological change (Michaels et al. (2014)). As a result, one might expect complementarity (or substitutability) between broadband access and the demand for (un)skilled labour.

The starting point of our analysis is that broadband access enables faster and broader diffusion of information about vacancy postings and is therefore likely to affect labour market outcomes. This paper investigates the effects of increased (fast)broadband internet coverage using Italian regional data from 2012 to 2019. We utilise information from a large dataset of online job advertisements (OJAs), which comprises approximately 5,000 OJAs annually, distributed across nearly 400 occupations in 20 NUTS2 Italian subdivisions between 2013 and 2019. This enables us to assess the overall response of posted vacancies to increased broadband connectivity and to detect changes in their skill content. In this regard, we focus on two key categories typically related to the internet-propelled ICT revolution: digital and cognitive skills. The former enable individuals' use of digital technologies (Vuorikari et al. (2022)) and are clustered around four basic skill categories: foundational, transversal, use of digital systems and tools, application of security measures, and informational processing. The latter are defined in terms of attention, memory, reasoning, problem-solving, perception, and language processing. They are essential for learning, decision-making, and adapting to new information or environments, and are typically frequent in occupations related to management, communication, accountancy, sales, and negotiation. The research question in this case concerns the potential complementarity between digital and cognitive skills in response to variations in broadband coverage.

Our measures of internet coverage will allow us to empirically disentangle the impact of relatively standard broadband access from that of fast connectivity, respectively defined as the fractions of households to whom a fixed broadband connection of at least either 30 or 100 Mbit/s in download speed is available.

We run a set of dynamic panel regressions where the dependent variable represents different features of posted vacancies, and the regressors include the instrumented index of broadband coverage, as well as occupational, time, and regional fixed effects. Using the same econometric methodology, we also investigate the contemporaneous responses of regional labour market data regarding hiring, layoffs, unemployment, employment, and working hours.

Related literature and contribution

We contribute to a rapidly growing body of literature examining the skill content of online job postings. Kureková et al. (2015) discuss methodological issues arising from online job vacancy data. Faberman et al. (2016) survey the early contributions, which focus on the US market. Egli et al. (2022) Deming and Kahn (2018), Hershbein and Kahn (2018) concentrate on the impact of skills on wages in the U.S. Lovaglio et al. (2018) focus on Italian job vacancies related to ICT. Azar et al. (2020) exploit OJAs to calculate labour market concentration and measure employer power in labour markets. Acemoglu et al. (2022), Squicciarini and Nachtigall (2021) and Samek et al. (2021) are concerned with the effect of AI on occupations. Modestino et al. (2020) investigate the Great Recession's impact on skills and experience requirements. Zilian et al. (2021) and Usabiaga et al. (2022) investigate skill polarisation patterns; finally, Mueller et al. (2024) explore the empirical relation between the duration of a vacancy and the entry wage of a filled position. To our knowledge, this is the first attempt to investigate the response of OJAs to changes in the digital infrastructure supply.

One distinctive feature of our analysis is that the time series of our data on internet coverage is relatively long, and the increased coverage of broadband and fast broadband took place almost simultaneously. Recent studies have examined the effects of increasing broadband speed, with a focus on firms' total factor productivity (TFP) responses. Fabling and Grimes (2021) found that fast broadband adoption increased the productivity of New Zealand firms over the 2010-2016 period. Cambini et al. (2023) document the positive effect of UFB on the productivity of Italian firms. Gillett et al. (2006) obtains similar results for Spanish firms. Kruse et al. (2022) found that broadband speed above 100 Mbit/s lowered unemployment rates by about 0.26 percentage points in the counties of the U.S. state of Tennessee from 2011 to 2015. We analyse several distinctive features of the labour market response to changing broadband speed.

Different strands of literature investigate the implications of broadband access on regional labour market outcomes. They are concerned with search and matching frictions, skill-biased technical change, employment and unemployment adjustments, and the differential role of broadband and fast broadband access.

A large consensus exists that internet access has reduced information asymmetries and labour market frictions. The observed sharp increase in firms' and job seekers' use of online job boards is generally associated with a generalised improvement in the recruitment process (see Bhuller et al. (2020) and references cited therein). Some contributions have investigated the use of the internet as a job search method (Denzer et al. (2021) and Gürtzgen et al. (2021)). In this vein, Bhuller et al. (2023) exploit quasi-experimental variation in the availability of broadband internet, as documented in the Norwegian National Broadband Policy of 2003, to investigate the effects of internet expansion on increased vacancy postings, their reduced average duration, and the increased job-finding probabilities of unemployed job seekers. This strand of literature is fundamentally concerned with identifying the effect of internet access on search and recruitment activities, which should be distinct from other effects stemming, for instance, from higher productivity growth (as documented in Czernich et al. (2011)). Our focus differs because we aim to understand the responses of OJAs to increased internet access coverage and the implications of upgrading the speed of connectivity from broadband to fast broadband.

Another important strand of literature focuses on the complementarity between broadband access and demand for skilled labour. Atasoy (2013) finds that internet access increased employment in US counties between 1999 and 2007, with more significant effects among college-educated workers and in industries and occupations that employ a higher proportion of college-educated workers. Akerman et al. (2015) exploit Norwegian data to show that broadband adoption is a skill-biased technological change, raising(lowering) the marginal productivity of (un)skilled workers. Bergeaud et al. (2021) find that in France, from 2000 to 2007, broadband availability raised the relative demand for high-skilled workers. They also find that broadband access led to the outsourcing of workers and provide evidence that, among these workers, high-skilled workers experienced salary gains, whereas low-skilled workers were worse off. Our focus differs because we investigate the skill composition of OJAs to detect the effects of internet coverage on the demand for digital and cognitive skills.

Our key results are summarised as follows. Internet connectivity does not appear to affect labour market variables such as employment and unemployment. Still, posted vacancies unambiguously increase, signalling a shift in the recruitment medium used by firms. We then investigate how broadband and fast-broadband shocks impact digital and non-digital occupations differently. Within this framework, we identify consistent patterns in the estimated responses of individual variables to the shock. Following broadband shocks, we do not observe a significant shift in the skill composition of posted vacancies. By contrast, fast broadband shocks induce heterogeneous responses for vacancies referring to digital and non-digital occupations. In brief, fast broadband shocks foster a tendency towards digitisation and, to a lesser extent, increased reliance on cognitive skills in non-digital occupations. In contrast, the opposite pattern is observed for occupations traditionally labelled as digital.

The remainder of the paper is organised as follows. Section 2 describes the data used, section 3 illustrates the methodology, section 4 presents the results, and finally section 5 concludes.

2 Data description

We restrict our analysis to the period from 2013 to 2019 for two reasons. First, vacancy data only became available in 2013. Second, we exclude the COVID-19 period to avoid potentially confounding effects from the pandemic, which could bias our results. NUTS2 is the lowest regional domain at which OJAS are available. We therefore aggregate all the remaining variables at this territorial level.

2.1 Online job advertisements (OJAs)

Lightcast, a leading company in web vacancy analysis, has provided OJAs data.[1] The data are extracted from primary sources, including specialised job boards, websites that provide public and private employment services, and job sections of national newspapers. OJAs are then analysed with Natural Language Processing algorithms and classified into specific taxonomies. The resulting dataset provides information on the occupation to which the OJA refers, the region where it is posted, the number of vacancies advertised for the specific occupation, and the type of skills required from potential applicants.

Our approach differs considerably from the standard task approach (Autor, 2013) to the labour market. Instead of identifying specific occupations (for example, digital occupations) defined by the Bureau of Labour Statistics, which details the characteristics of over 900 different occupations based on an analysis of job roles in the USA, we examine the skill content of occupations.

The skills are extracted from the text of OJAs and classified according to a proprietary taxonomy, then converted into the ESCO skills classification. ESCO[2] is an initiative by the EU that provides a taxonomy or structured vocabulary for Occupations, Skills and competences, and qualifications. The occupation pillar of ESCO corresponds to the ISCO occupation taxonomy. For our purposes, we focus on digital and cognitive skills here. ESCO provides a specific taxonomy of digital skills ((Esco, 2022)). As cognitive skills, we consider groups S2 (Information skills) and T2 (thinking skills and competences). The group S2, Information skills, deals with the ability to effectively find, evaluate, and utilise information. In contrast, T2, Thinking skills and competences, encompasses higher-level cognitive abilities such as critical thinking, problem-solving, and decision-making.

For each occupation in a certain sector, multiple vacancies are posted in a given year and region. Skills are observed within individual job vacancies referring to a specific occupation, and we classify such skills for each occupational category. More formally, in the remainder of the paper, the generic variable $y_{i,s,r,t}$, where the subscripts i,s, r, t respectively define

[1] `https://lightcast.io/resources/research`

[2] The acronym stands for European Skills, Competences, Qualifications and Occupations. More details can be found at `https://esco.ec.europa.eu/en`.

the occupational code, the sector, the region, and time, will take the following alternative definitions :

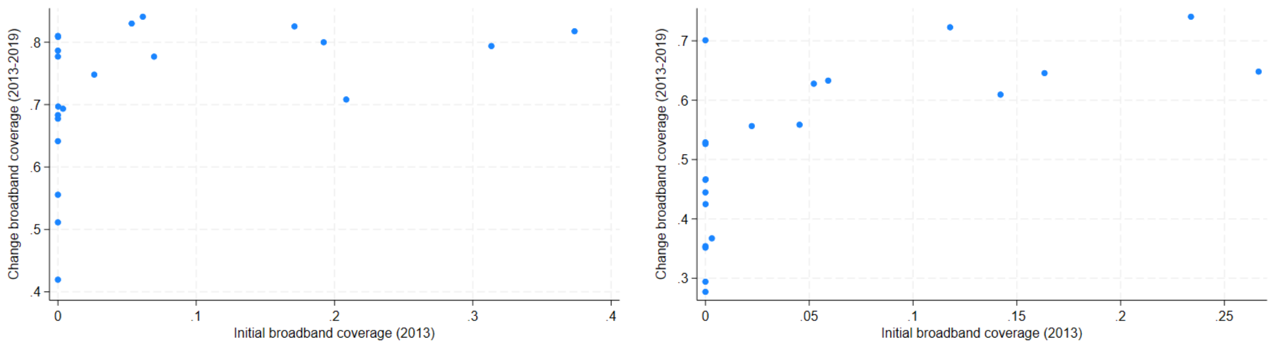
1. The total number of posted online vacancies (*Total vacancies*).
2. The number of vacancies that require at least one x_j skill, where j refers to either digital or cognitive skills (X_j *vacancies*).
3. The share of vacancies that require at least one x_j skill (*Share of* x_j *vacancies*).
4. The total number of x_j skills identified in the occupation (*Total* x_j *skills*). This is obtained by aggregating the relevant skills across vacancies referring to a specific occupation.
5. The variable X_j *skill variety* , whose features are better understood with reference to the variable that calculates the total number of skills. Consider the following example. If our original data for occupation i in region r, sector s and at time t report ten vacancies, each listing the digital skills A and B, then the variable *Total digital skills* will have a value of 20, reflecting the cumulative count of all skill mentions (10 vacancies × 2 skills). In contrast, the variable *digital skill variety* will have a value of 2, capturing the distinct digital skills required, regardless of how frequently they appear across vacancies for a given occupation. *Ceteris paribus*, an increase in the variable *Digital skill variety* would indicate that new and different digital skills are being demanded in online job postings. In contrast, an increase in *Total digital skills* could be driven by either an increase in vacancies requiring the same digital skills or by the rise in the number of different skills, as signalled by the variable *Digital skill variety*.
6. The variable X_j *skill dispersion ratio*, which identifies the ratio between the variables X_j *skill variety* and *Total* x_j *skills*. The example used to interpret the *Digital skill variety* variable above implies that the corresponding *Digital skill dispersion ratio* is $1/5$. Ceteris paribus, if the value of *Digital skill variety* doubled, the corresponding increase in the *Digital skill dispersion ratio* would signal a greater differentiation in the type of skills required in the vacancies referring to a specific occupation.

2.2 Broadband data

Broadband data were obtained from Point Topic (2024) at the EUROSTAT NUTS3 level between 2012 and 2019 and then aggregated at the NUTS2 level. For each region, our two connectivity measures identify the share of households with broadband access "capable of realistically achieving download speeds of at least 30 Mbit/s and 100 Mbit/s, respectively. We refer to the former as broadband and the latter as fast broadband.

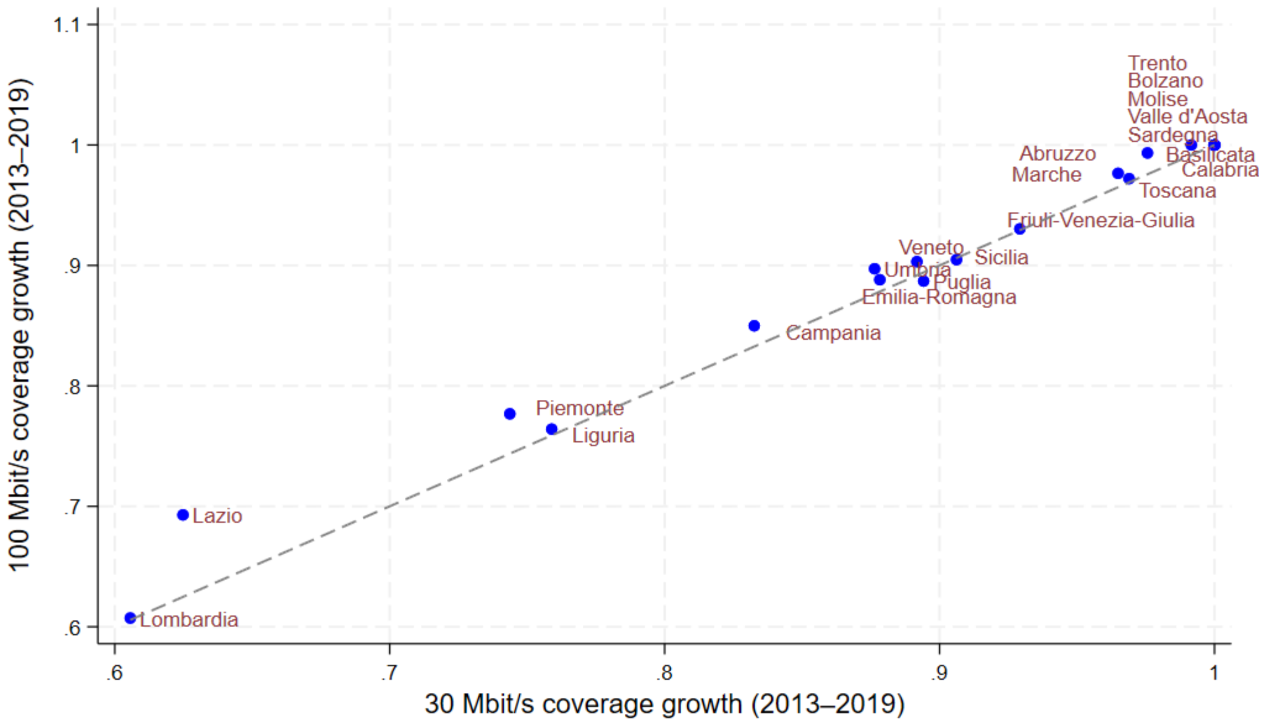
Maps 1a and 1b in Figure 1 show the increase in (ultrafast)broadband coverage across the NUTS3 regions. Figures 1 and 2 document dynamics in the degree of (fast)broadband coverage and the strong correlation between 100 Mbit/s and 30 Mbit/s broadband coverage growth in Italian regions.

Figure 1: Broadband coverage dynamics



(a) 30 (b) 100

Figure 2: Correlation between 100 Mbit/s and 30 Mbit/s broadband coverage growth in Italian regions (2013-2019)



2.3 The digital Revealed Comparative Advantage index (RCA)

Our analysis could greatly benefit from understanding the relative importance of reliance on a specific type of skill, in this case, digital skills, in vacancy postings. In this regard, the digital

Revealed Comparative Advantage index provides valuable insights (Lennon et al. (2023)). The RCA measure was first developed in international trade theory.[3] More recently, RCA has been translated into the economic geography literature to describe regions' specialisation in productive activities (see van Dam et al. (2023) for an overview of the literature and the most recent advances). In the labour market, a notable application of this concept is provided by Alabdulkareem et al. (2018)[4]. Following Lennon et al. (2023) we have constructed the RCA index for digital skills.[5] More formally, let $j = 1...m$ define occupations, $i = 1...n$ define the skill set, D define the group of digital skills which is a partition of the skill set, and $S_{i,j}$ define the skill i in occupation j.

$$RCA_{D,j} = \frac{\frac{\sum_{i \in D} S_{ij}}{\sum_{i=1}^{n} S_{ij}}}{\frac{\sum_{j=1}^{m} \sum_{i \in D} S_{ij}}{\sum_{j=1}^{m} \sum_{i=1}^{n} S_{ij}}}$$

The numerator of the equation defines the specialisation of a certain occupation j in the group of digital skills (all skills part of the digital group $i \in D$). In contrast, the denominator defines the average aggregate specialisation (which can be considered as the market specialisation). The RCA has a range $[0, +\infty)$ and has a natural focal point at 1. If $RCA_{D,j} > 1$, then occupation j is specialised in digital skills more than the average occupation in the market.

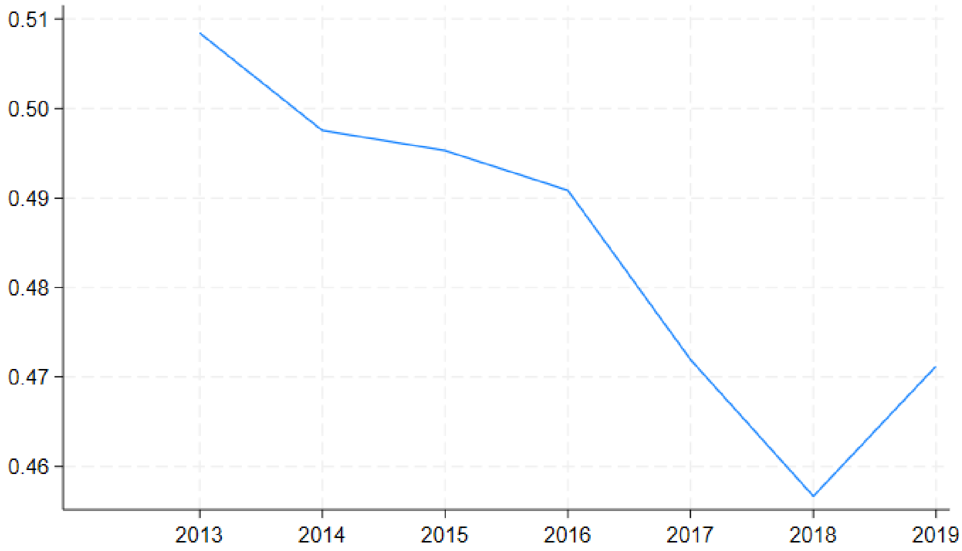
We have then dichotomised the $RCA_{D,j}$ index by constructing a dummy variable $dRCA_j$ that takes the value of 0 if $RCA_{D,j} < 1$ and 1 otherwise. We classify digital occupations as those with $dRCA_j = 1$. Figure 3 shows that digital occupations account for a fraction of vacancies per annum, which is close to 50 per cent, with a tendency to decline over time.

[3]The rationale was to use post-trade measures to infer the comparative advantages in the production of traded goods of a region in a multilateral context.

[4]There is a clear analogy with trade theory. In trade theory countries produce several type of goods which then trade. The issue is how to measure the specialization of the production using trade flows. In our context we can think of occupations as countries and skills as the goods in which countries are specialized.

[5]The RCA was originally computed at the most granular occupation level; our vacancy data requires aggregation to broader occupational categories, such as the 4-digit ISCO level.

Figure 3: Share of total vacancies with associated digital Revealed Comparative Advantage (2013-2019)



3 Methods

We estimate the following model:

$$y_{i,r,s,t} = \beta_0 + \beta_1 y_{i,r,s,t-1} + \beta_2 x_{r,t} + \beta_3 x_{r,t-1} + \beta_4 (dRCA_{i,r,s,t} x_{r,t}) + \gamma_t + \alpha_{r,i} + \varepsilon_{r,i,t} \quad (1)$$

where x_{rt} is an index of (fast)broadband coverage; $(RCA_{i,r,s,t} \times x_{r,t})$ is the interaction term that we incorporate in the estimates by imposing ε =1 (ε=0 otherwise). The interaction term allows us to estimate the potentially distinct effects for digital (δ=1 if RCA>1) and non-digital (δ=0 if RCA $\leq$1) occupations (; γ_t, α_r, α_s and α_i respectively denote time, regional, sectoral, and occupational fixed effects.

3.1 Instruments

Estimates of the effects of broadband on economic outcomes are subject to concerns about endogeneity. For instance, local economic shocks may simultaneously impact the decision to roll out broadband coverage and firms' vacancy postings, leading to biased OLS estimates. The standard solution to this problem is identifying instrumental variables and employing a two-stage estimation strategy. As pointed out in Kolko (2012), installing or upgrading broadband requires suppliers to bear fixed costs. Instrumental variables should, therefore, affect these costs. However, according to the instrument exclusion restriction, they should neither impact the dependent variable outside their effect on broadband nor be endogenous to other factors that matter in the estimation exercise. His chosen instrument is the average slope of the local terrain, which typically raises the cost of broadband deployment. Several contributions rely on the fact that broadband roll-out typically is the offspring of previously established infrastructures, whose availability lowers deployment costs. Czernich et al. (2011) rely on pre-existing fixed-line telephony and cable TV networks to instrument the diffusion of broadband networks. Cambini et al. (2023) use data on broadband coverage to investigate the effects of ultrafast broadband on firms' productivity in Italy. They instrument their broadband series, exploiting the distance of each municipality from the nearest node in the telecommunications network. These nodes are upgraded facilities of the old telephone communication network established around the early 2000s.

Given that we rely on the same data source for broadband coverage as Cambini et al. (2023), it seems natural to follow their approach. Still, we face an additional difficulty because online posting data are available at the regional level. We are therefore compelled to develop an instrument that somehow averages out the distances of municipalities in the regions from the nearest nodes. The variable $instrument1\_r, t$ is constructed to proxy for broadband exposure intensity at the regional-year level, based on the geographical distance between municipalities and the 35 telecommunications nodes that characterise the Italian network, weighted by municipal population, and adjusted to account for the number of nodes from which local broadband supply originates. It is computed as follows. Each municipality z is geolocalised, and the distance $d_{z,j}$ of the municipality from each of the 35 known broadband nodes j is calculated using geodesic distance. Using the STATA command $geodist$, the closest node is identified by $\min_j(d_{z,j})$. All municipalities within the same region and year are aggregated to compute:

$$\texttt{weighted distance}_{r,t} = \sum_{z \in (r,t)} \frac{\texttt{population}_z}{1 + \min_j(d_{z,j})}$$

The instrument is defined as:

$$\texttt{instrument1}_{r,t} = \texttt{weighted distance}_{r,t} \times \texttt{node\_count}_{r,t}$$

where $node\_count_{r,t}$ defines the number of nodes within a minimum distance for at least one municipality belonging to the region. This latter variable should capture the competition-enhancing effect of the number of nodes on the broadband supply.

We have also decided to compute an alternative $instrument2\_r, t$ variable focusing on each region's urban centres that are relatively large. It is calculated as follows.

$$Instrument2_{r,t} = \frac{(P_{r,t} \times I_{r,t})}{(1 + D_{r,t})} \tag{2}$$

where:

- $N_{r,t}$ = Number of large urban centres (pop $\geq 90,000$) in region r, year t.

- $P_{r,t}$ = Total population in these large urban centers in region r, year t.

- $I_{r,t}$ = Average number of infrastructure nodes within 50 km from each large urban centre in region r, year t.

- $D_{r,t}$ = Average distance from each large urban centre to infrastructure nodes within 50 km in region r, year t.

Right from the beginning, we would like to discuss possible violations of the instrument exclusion restriction. First, both instruments include the population of municipalities(urban centres) to weight the distance-from-node indicators. One might argue that, by doing this, we are instrumenting broadband coverage with the regional population size. In principle, this should not happen for at least two reasons. First, the distance measures and the number of relevant nodes drive a wedge between the two instrumental variables and the actual size of regional population variables. Second, the instrumental variables typically change due to internal migration episodes, which do not alter the size of the regional population. Another issue, raised in Cambini et al. (2023), is that some economic factor that drove the geographical distribution of nodes in the past might also affect, in a long-term perspective, the posting of online vacancies. In this case, by including time-varying population measures in our instruments, we can maintain the regional fixed effects that should control for this potential impact in our regressions.

The first-stage regression is estimated using Ordinary Least Squares (OLS) with high-dimensional fixed effects, as specified by the reghdfe command in STATA. We obtain that $instrument1\_r,t$ is a good instrument for broadband but does not pass the test for the fast broadband variable. The opposite results hold for the $instrument2\_r,t$ variable. In the following, we shall therefore use $instrument1\_r,t$ and $instrument2\_r,t$ as instruments for the broadband and fast broadband variables, respectively. The results reported in the Tables 3 and 4 confirm their validity as instruments.

Due to the skewness of the online posting data, as documented in the Appendix, the second-stage regression cannot be estimated using the two-stage least squares method. Therefore, we use the Poisson Pseudo Maximum Likelihood estimator with high-dimensional fixed effects. Standard errors are clustered at the regional level. To obtain robust inference, we use a bootstrap with 1000 replications. This ensures that the instrumental variable strategy is robust to overdispersion and excess zeros in the dependent variable while allowing for flexible fixed-effects specifications. For each dependent variable, the first-stage results are presented in the Appendix, Section 5.

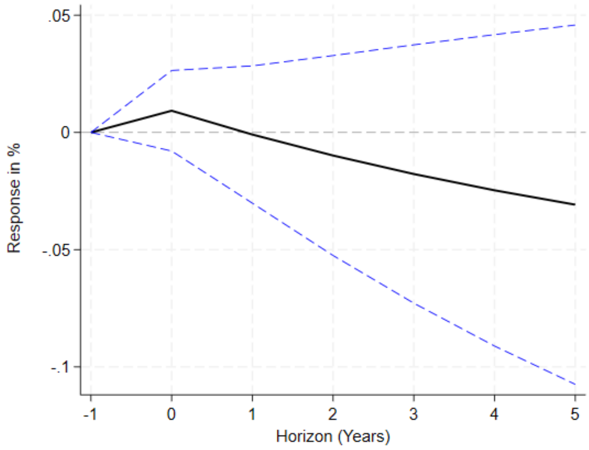
In the second stage of our estimates, we apply the control function approach (Wooldridge (2015)) to test for endogeneity of the regressor. In practice, this requires that the residuals from the first-stage regression be included as additional controls in the second-stage regression. Broadband endogeneity cannot be rejected when these residuals are statistically significant.

4 Results

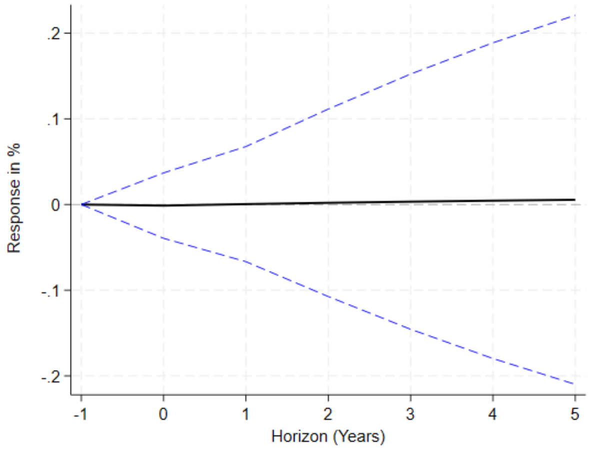
Presentation of our results unfolds as follows. First, we document the response of macro labour variables: *Employment*, *Unemployment* and *Total vacancies*. Second, we focus on online postings to discuss the changes in the composition of labour demand, based on the empirical model depicted in 1. Our dynamic models yield estimates that are best represented by plotting IRFs.

4.1 Labour market macro variables

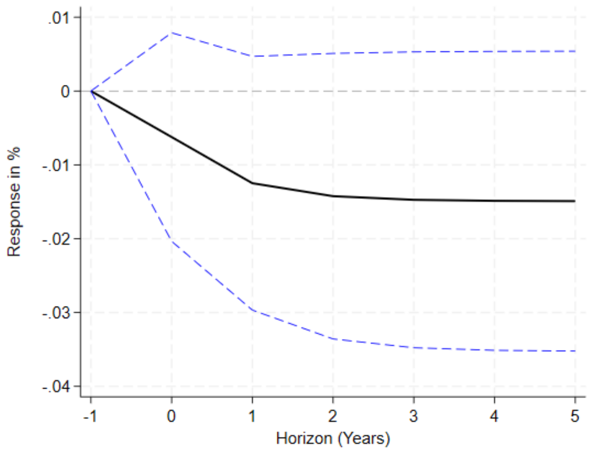
Figures 4 and 5 show that (fast)broadband shocks do not seem to have an impact on employment and unemployment, but they do have a sizable and permanent positive effect on job postings, suggesting that increased internet connectivity essentially induced a more intensive use of the internet as a medium for hiring in the labour market.



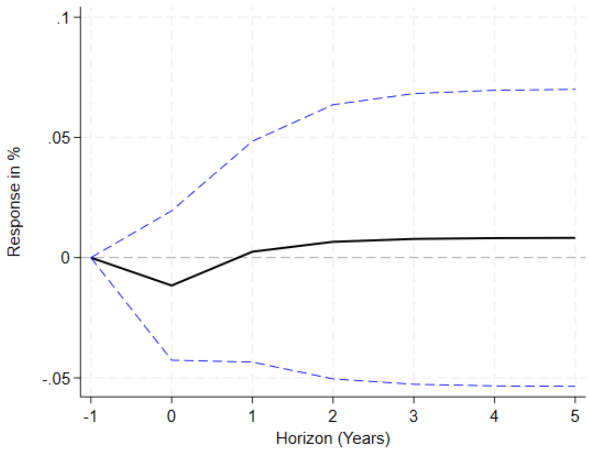
(a) Employment – 30 Mbit/s



(b) Employment – 100 Mbit/s



(c) Unemployment Rate – 30 Mbit/s



(d) Unemployment Rate – 100 Mbit/s

Figure 4: Impact of 1% broadband diffusion on employment and unemployment. Left column: 30 Mbit/s coverage; right column: 100 Mbit/s coverage.

4.2 The response of labour demand composition through the lens of online vacancies

4.2.1 Digital skills

Consider first the distinct responses of Total vacancies that we obtain for digital and non-digital occupations (Figure 6). Broadband shocks elicit identical responses; however, we do observe significant differences following a fast broadband shock. In this latter case, the response estimated for digital occupations is insignificant, whereas a substantial increase characterises non-digital occupations.

Following a broadband shock (see Figures 7 and 8), *Digital vacancies* increase unambiguously, but their share of the total number of online vacancies remains constant. The *Digital skill variety* variable also increases, while the point estimate for the *Digital skill dispersion ratio* decreases, but remains statistically insignificant. All in all, this set of results suggests that the broadband shock raises demand for digital skills, which, in turn, tend to be more differentiated. However, these outcomes do not signal a substantial change in the digital-skill composition of labour demand, as indicated by the non-significant responses of the variables 'Share of digital vacancies' and 'Digital skill dispersion ratio'. The interaction term does not reveal significant differences between digital and non-digital occupations, with the notable exception of the "Share of digital vacancies" variable. In this case, we observe an increase for non-digital occupations, and an insignificant response otherwise.

The IRFs to a fast broadband shock tend to be quite different (Figure 9). On average, *Digital vacancies* do rise on impact, but the long-run response is not significantly different from zero. However, we also obtain that *Digital vacancies* increase in non-digital sectors and decrease otherwise. The share of online vacancies in the total number tends to decline on average, but this masks the fact that its variation is insignificant for non-digital sectors. The *Digital skill variety* variable increases, but the strength of its adjustment is significantly smaller than the one we observe in response to a broadband shock. Furthermore, we do not observe a significant response for digital occupations. The *Digital skill dispersion ratio* decreases, but the change is insignificant. This is due to what we observe for non-digital occupations, whereas this variable falls for digital occupations.

4.2.2 Cognitive skills

Following a broadband shock, Cognitive vacancies increase, and their share of the total number of online vacancies also rises.[6] The *Cognitive skill variety* variable also increases, and the *skill dispersion ratio* unambiguously falls. These two combined results suggest that,

[6] This happens even if the total number of cognitive skills identified in the vacancy significantly increases. Results available upon request.

even if additional new skills are required in response to the shock, posted vacancies are less differentiated. The analysis of interaction terms does not reveal significantly heterogeneous effects between digital and non-digital occupations.

Following a fast broadband shock, the *Cognitive vacancies* variable tends to fall, but its adjustment is not significantly different from zero. The adjustment of non-digital occupations drives this result, whereas a fall occurs in digital occupations. Relative to the total number of online vacancies, the average response of *Cognitive vacancies* is muted. Still, we observe an increase in non-digital occupations, accompanied by a negative, albeit insignificant, response in digital sectors.[7] The average point estimate of the *Cognitive skill variety* variable increases, but the estimate lacks precision and is marginally insignificant. This result is driven by the response observed for the digital occupations, whereas we obtain an increase for non-digital occupations. Finally, the *Skill dispersion ratio* is negative but insignificant on average; however, we estimate a significant decline for digital occupations.

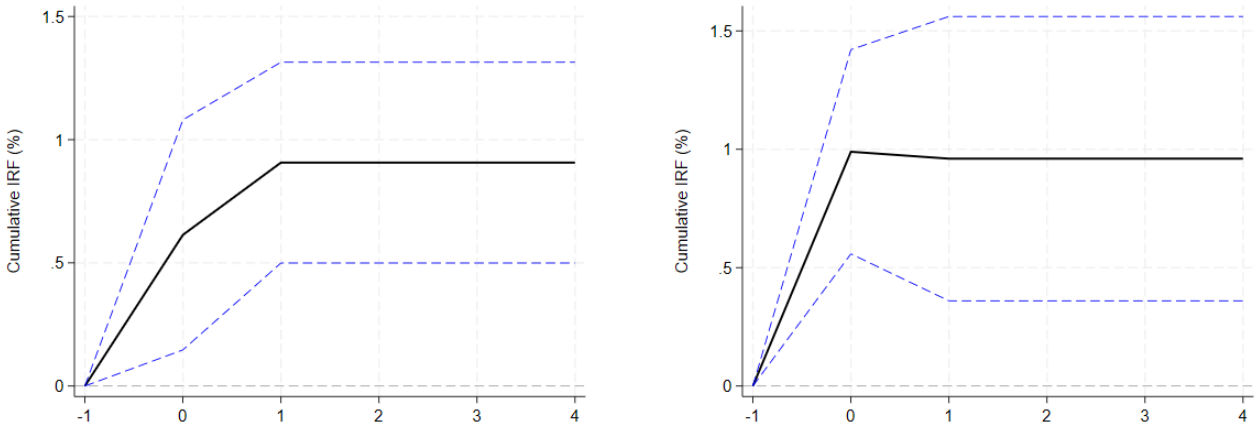
4.2.3 Summing up

To provide a meaningful synthesis of our results, we must distinguish between broadband and fast-broadband shocks, and between digital and non-digital occupations. Within this matrix, we can identify consistent patterns in the estimated responses of individual variables to the shock.

To begin with, vacancies for digital and non-digital occupations exhibit almost identical responses to broadband shocks. In this case, the overall increase in vacancy postings is associated with a substantial stability of their digital-skill composition. A similar result is obtained when examining cognitive skills.

By contrast, fast broadband shocks induce heterogeneous responses for vacancies referring to digital and non-digital occupations. To begin with, for digital occupations and unlike non-digital ones, we observe a muted response in the number of posted vacancies. Furthermore, we observe that digital occupations are characterised by negative reactions for all the variables describing changes in the demand for digital skills. We observe a reduction in the number of vacancies that require at least one digital skill; there is no increase in the *Variety of digital skills*, and the *Digital skill dispersion ratio* also falls, suggesting that postings are less differentiated. These adjustments typically follow an opposite pattern for non-digital occupations. One possible takeaway is that fast broadband shocks induce a tendency towards digitisation in non-digital occupations, whereas the opposite pattern is observed for the traditionally digital occupations.

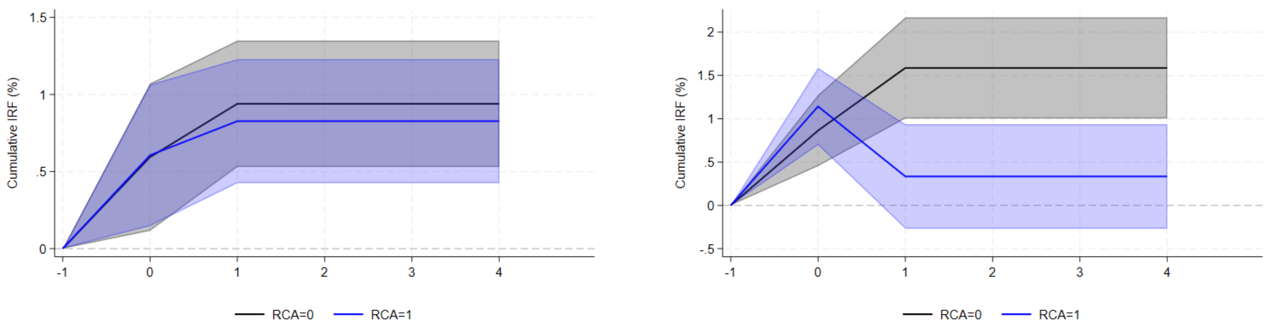
[7]The total number of cognitive skills identified in the vacancy significantly falls. Results available upon request.



(a) 30 Mbit/s broadband diffusion

(b) 100 Mbit/s broadband diffusion

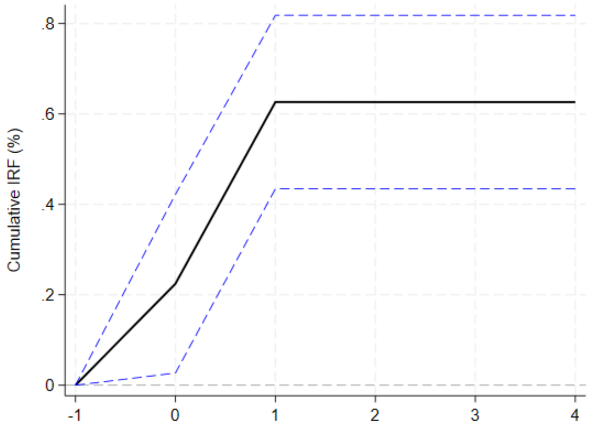
Figure 5: Impact of 1 % broadband diffusion on Total vacancies (IV estimates, 4-digit ISCO classification). Panel (a) shows the effect of 30 Mbit/s coverage; panel (b) shows the effect of 100 Mbit/s coverage.



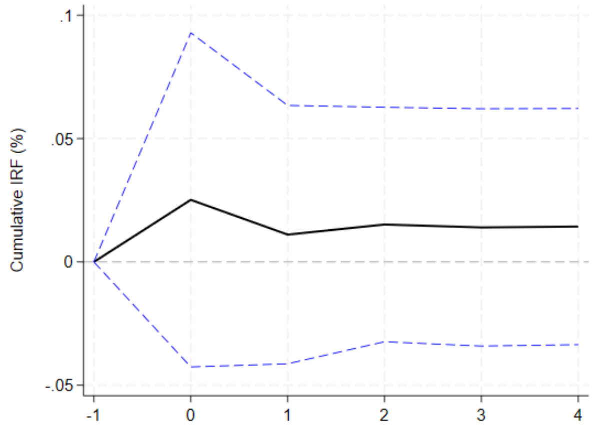
(a) 30 Mbit/s broadband diffusion

(b) 100 Mbit/s broadband diffusion

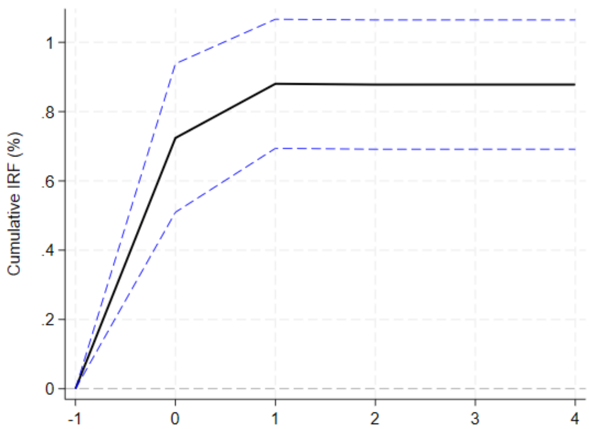
Figure 6: Impact of 1 % increase in broadband diffusion on total vacancies (IV estimates, 4-digit ISCO classification). Panel (a): 30 Mbit/s; Panel (b): 100 Mbit/s. Black line = effect when RCA = 0, Blue line = effect when RCA = 1.



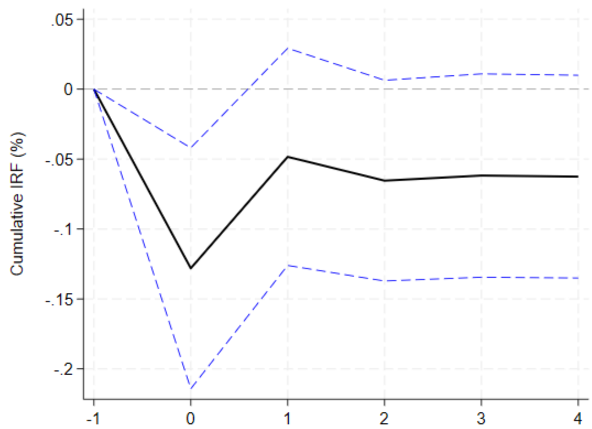
(a) Digital vacancies



(b) Share of digital vacancies

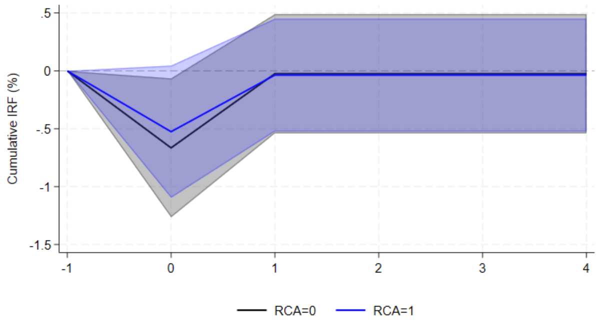


(c) Digital skill variety

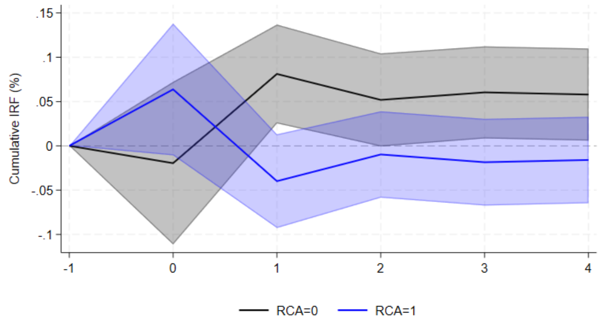


(d) Digital skill dispersion ratio

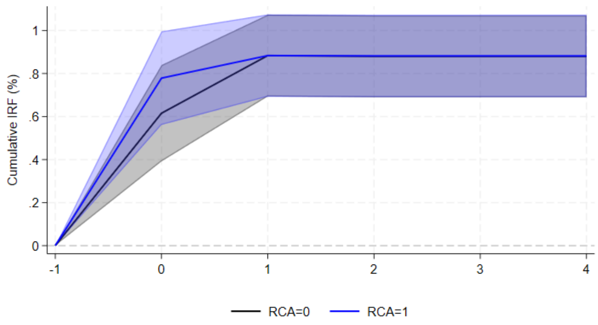
Figure 7: Impact of 1 % diffusion of 30 Mbit/s broadband on: (a) Digital vacancies (4-digit ISCO classification); (b) Share of digital vacancies (4-digit ISCO classification); (c) Digital skill variety (IV estimates, 4-digit ISCO classification); (d) Digital skill dispersion ratio (4-digit ISCO classification.
Note: The x-axis (Horizon) is expressed in years.



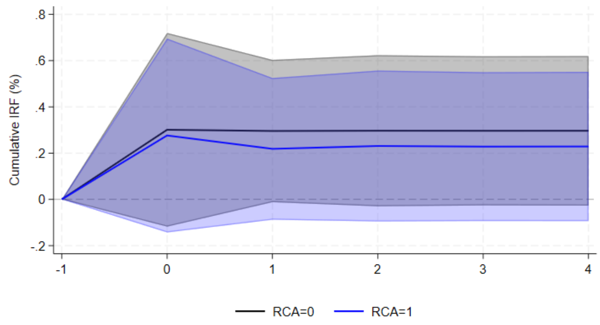
(a) Digital vacancies



(b) Share of digital vacancies

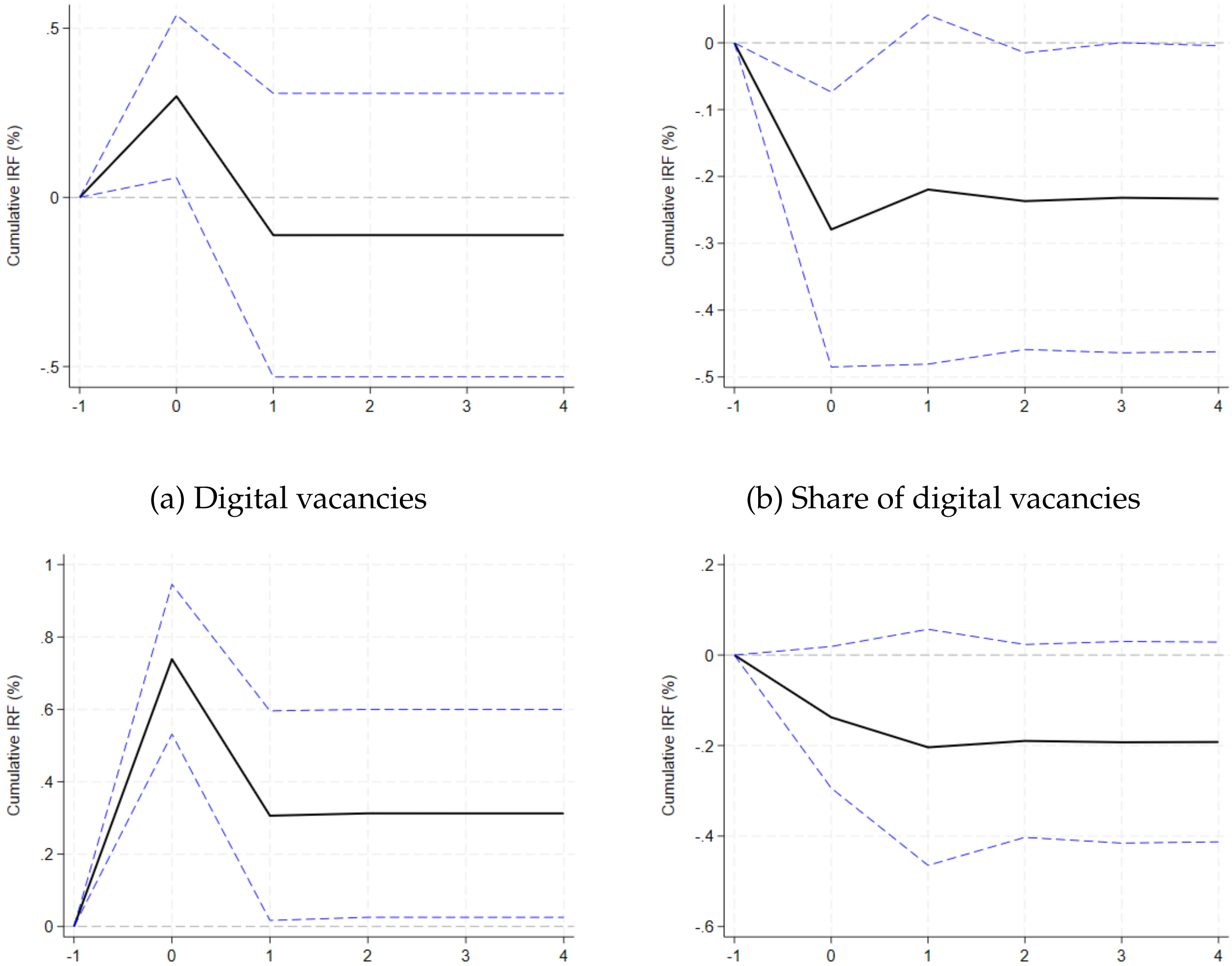


(c) Digital skill variety



(d) Digital skill dispersion ratio

Figure 8: Impact of 1 % increase in 30 Mbit/s broadband diffusion on: (a) Digital vacancies (IV estimates, 4-digit ISCO classification); (b) Share of digital vacancies (IV estimates,4-digit ISCO classification); (c) Digital skill variety (IV estimates, 4-digit ISCO classification); (d) Digital skill dispersion ratio (IV estimates, 4-digit ISCO classification). Black line: RCA = 0, Blue line: RCA = 1.
Note: The x-axis (Horizon) is expressed in years.



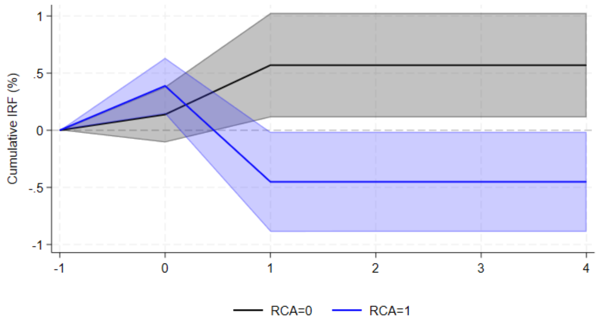
(a) Digital vacancies

(b) Share of digital vacancies

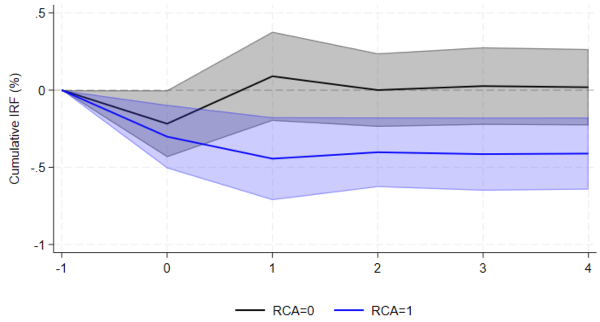
(c) Digital skill variety

(d) Digital skill dispersion ratio

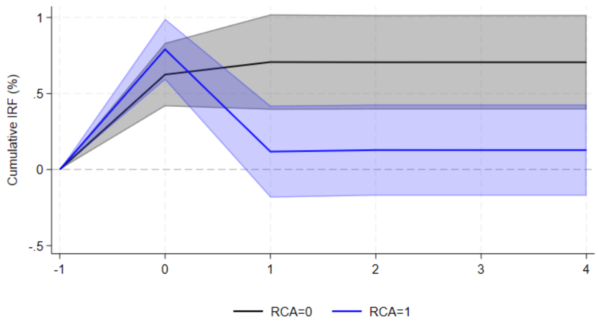
Figure 9: Impact of 1 % diffusion of 100 Mbit/s broadband on: (a) Digital vacancies (4-digit ISCO classification); (b) Share of digital vacancies (IV estimates, 4-digit ISCO classification); (c) Digital skill variety (IV estimates, 4-digit ISCO classification); (d) Digital skill dispersion ratio (4-digit ISCO classification).
Note: The x-axis (Horizon) is expressed in years.



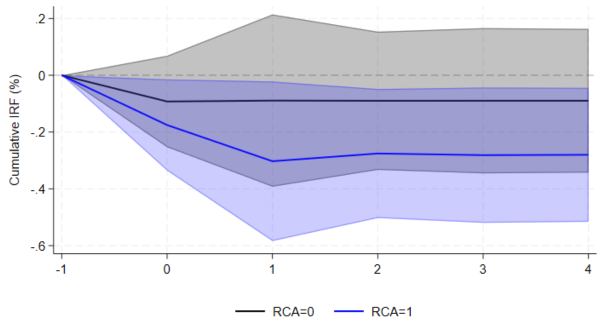
(a) Digital vacancies



(b) Share of digital vacancies

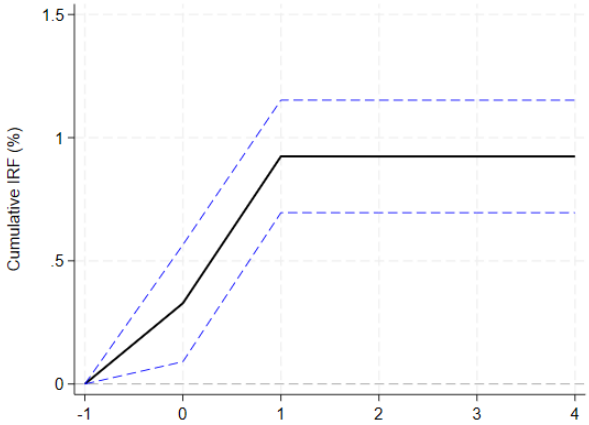


(c) Digital skill variety

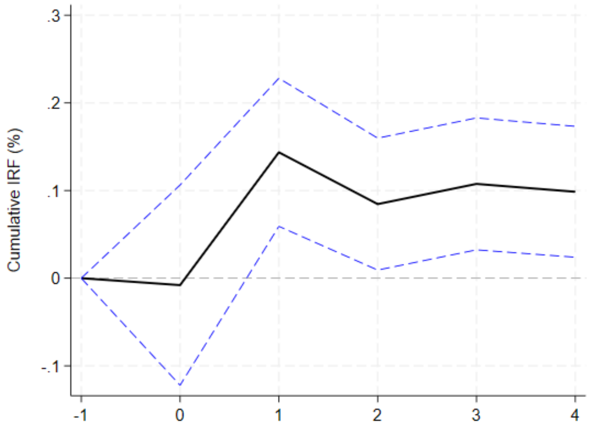


(d) Digital skill dispersion ratio

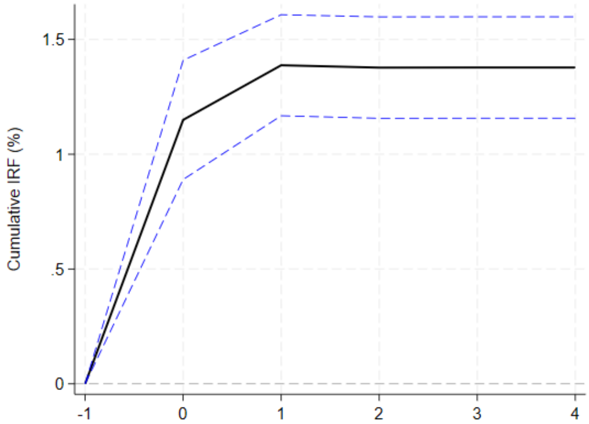
Figure 10: Impact of 1 % increase in 100 Mbit/s broadband diffusion on: (a) Digital vacancies (4-digit ISCO classification); (b) Share of digital vacancies (IV estimates, 4-digit ISCO classification); (c) Digital skill variety (IV estimates, 4-digit ISCO classification); (d) Digital skill dispersion ratio (4-digit ISCO classification). Black line: RCA = 0, Blue line: RCA = 1. Note: The x-axis (Horizon) is expressed in years.



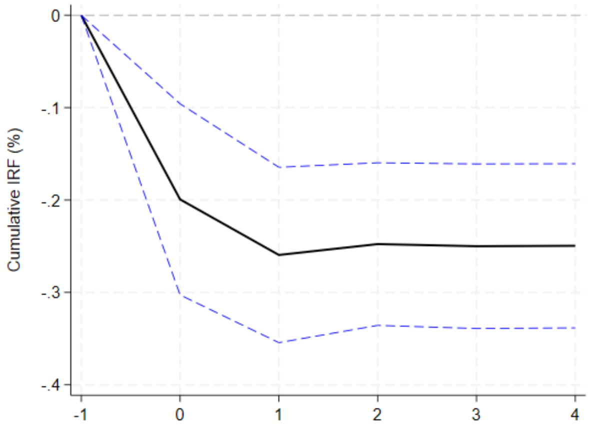
(a) Cognitive vacancies



(b) Share of cognitive vacancies

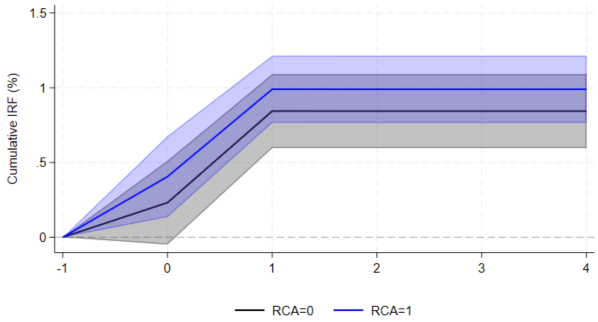


(c) Cognitive skill variety

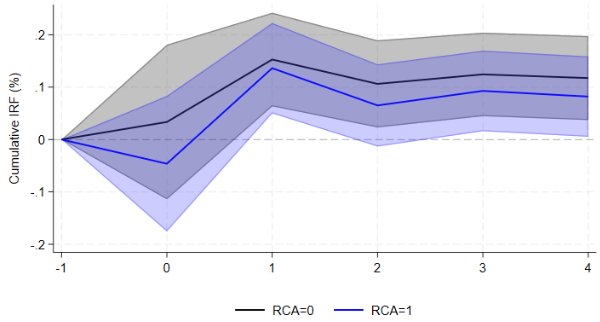


(d) Cognitive skill dispersion ratio

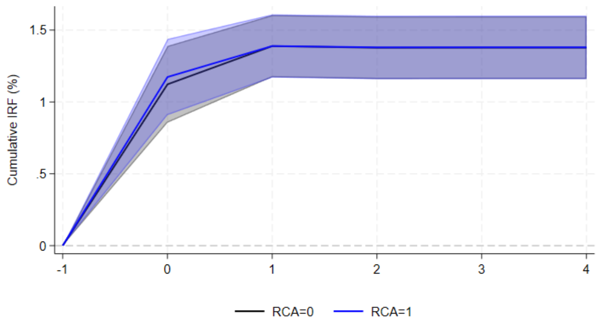
Figure 11: Impact of 1 % diffusion of 30 Mbit/s broadband on: (a) Cognitive vacancies (4-digit ISCO classification); (b) Share of cognitive vacancies (4-digit ISCO classification); (c) Cognitive skill variety (IV estimates, 4-digit ISCO classification); (d) Cognitive skill dispersion ratio (4-digit ISCO classification).
Note: The x-axis (Horizon) is expressed in years.



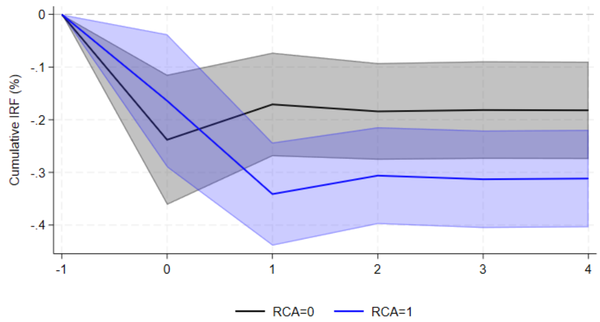
(a) Cognitive vacancies



(b) Share of cognitive vacancies

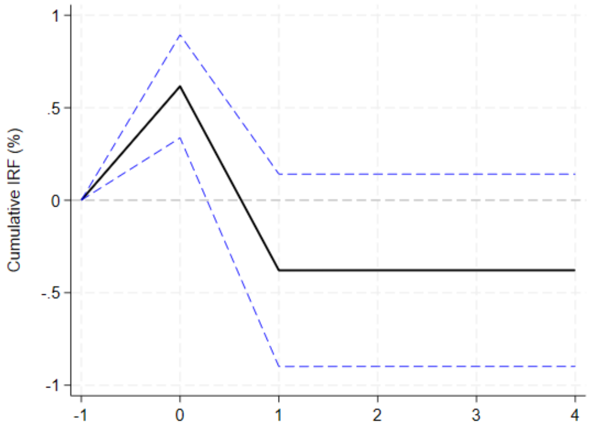


(c) Cognitive skill variety

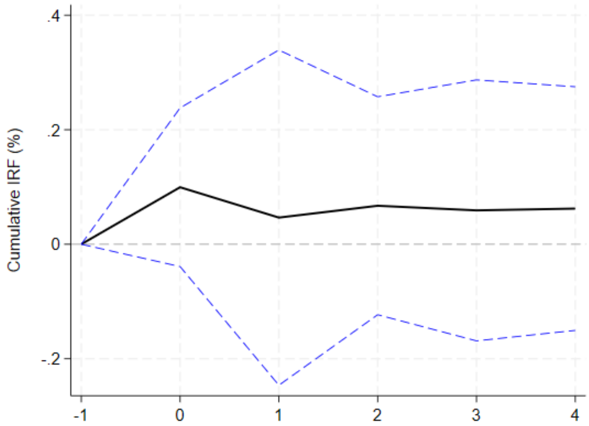


(d) Cognitive skill dispersion ratio

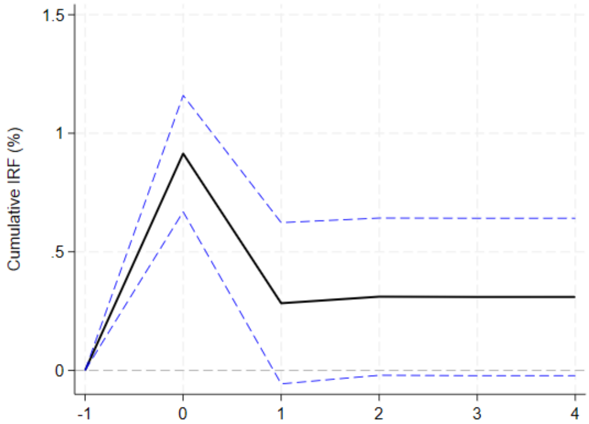
Figure 12: Impact of 1 % increase in 30 Mbit/s broadband diffusion on: (a) cognitive vacancies (4-digit ISCO classification); (b) Share of cognitive vacancies (IV estimates, 4-digit ISCO classification); (c) cognitive skill variety (IV estimates, 4-digit ISCO classification); (d) cognitive skill dispersion ratio (4-digit ISCO classification). Black line: RCA = 0, Blue line: RCA = 1.
Note: The x-axis (Horizon) is expressed in years.



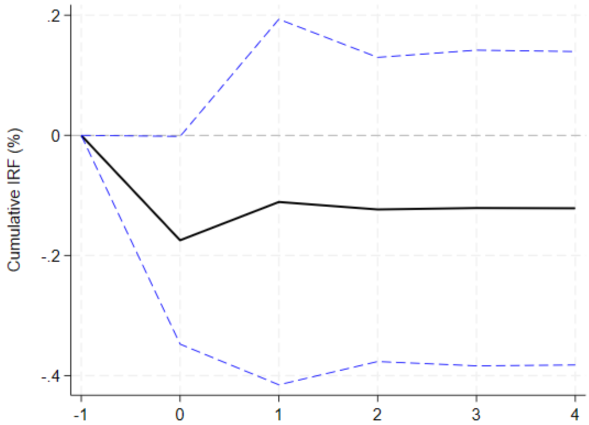
(a) Cognitive vacancies



(b) Share of cognitive vacancies

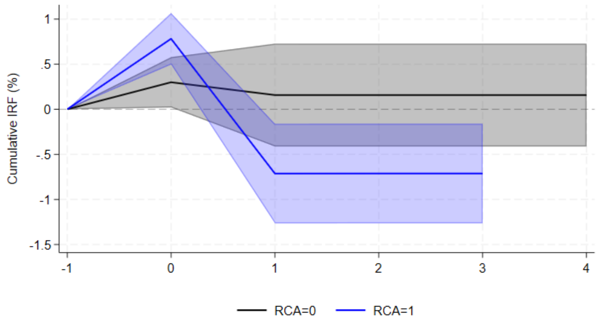


(c) Cognitive skill variety

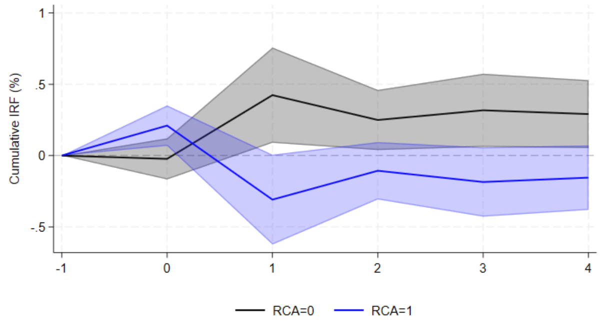


(d) Cognitive skill dispersion ratio

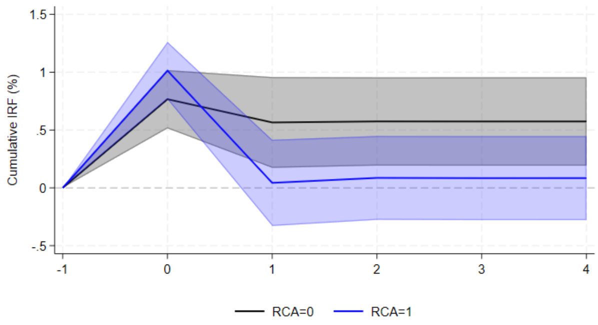
Figure 13: Impact of 1 % diffusion of 100 Mbit/s broadband on: (a) Cognitive vacancies (4-digit ISCO classification); (b) Share of cognitive vacancies (4-digit ISCO classification); (c) Cognitive skill variety (IV estimates, 4-digit ISCO classification); (d) Cognitive skill dispersion ratio (4-digit ISCO classification).
Note: The x-axis (Horizon) is expressed in years.



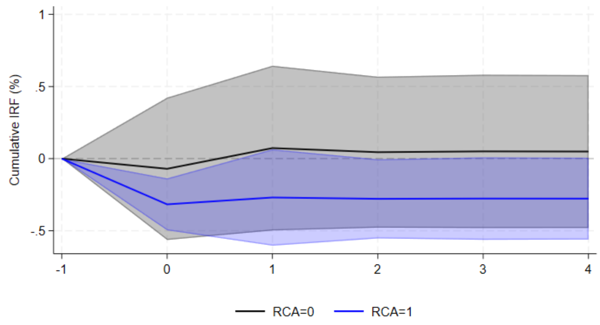
(a) Cognitive vacancies



(b) Share of cognitive vacancies



(c) Cognitive skill variety



(d) Cognitive skill dispersion ratio

Figure 14: Impact of 1 % increase in 100 Mbit/s broadband diffusion on: (a) cognitive vacancies (4-digit ISCO classification); (b) Share of cognitive vacancies (IV estimates, 4-digit ISCO classification); (c) cognitive skill variety (IV estimates, 4-digit ISCO classification); (d) cognitive skill dispersion ratio (4-digit ISCO classification). Black line: RCA = 0, Blue line: RCA = 1.
Note: The x-axis (Horizon) is expressed in years.

5 Conclusions

The paper contributes to the analysis of labour market responses to the expansion of (fast)broadband coverage, with a specific focus on Italy. We offer a new perspective on the skill content of online job vacancy postings, with a particular focus on digital and cognitive skills.

In addition to the measure of total online vacancies, for both cognitive and digital skills, we primarily focus on four indicators: the number of vacancies that require at least one skill, the skill variety index, and the skill dispersion ratio. We also obtain distinct estimates for digital and non-digital occupations.

An increase in broadband and fast broadband connectivity has an expansionary effect on the total number of online vacancies. The responses of the other variables to changes in our measures of internet connectivity are pretty different. Broadband shocks do not significantly impact the skill composition of job postings. In contrast, fast broadband shocks increase the digital and cognitive skill content of vacancies posted for non-digital occupations. We also observe that new skills are requested in job postings, and the skill content of individual vacancies tends to be more differentiated. The estimates for digital occupations reverse these results. In a sense, it seems that fast broadband shocks may foster digitisation in traditional occupations. In contrast, postings for occupations identified as digital suggest that firms do not seek to deepen the human capital of new hires. Was this outcome due to a weaker competitive position of Italian firms that supply relatively advanced digital services, and/or to their substitution with international competitors whose services become more easily accessible in consequence of increased fast broadband connectivity? We leave this for future research.

References

Acemoglu, D., 2002. Technical change, inequality, and the labor market. Journal of economic literature 40, 7–72.

Acemoglu, D., Autor, D., Hazell, J., Restrepo, P., 2022. Artificial intelligence and jobs: Evidence from online vacancies. Journal of Labor Economics 40, S293–S340.

Akerman, A., Gaarder, I., Mogstad, M., 2015. The skill complementarity of broadband internet. The Quarterly Journal of Economics 130, 1781–1824.

Alabdulkareem, A., Frank, M.R., Sun, L., AlShebli, B., Hidalgo, C., Rahwan, I., 2018. Unpacking the polarization of workplace skills. Science Advances 4, eaao6030. doi:10.1126/sciadv.aao6030.

Atasoy, H., 2013. The effects of broadband internet expansion on labor market outcomes. ILR review 66, 315–345.

Autor, D.H., 2001. Wiring the labor market. Journal of Economic Perspectives 15, 25–40.

Autor, D.H., 2013. The "task approach" to labor markets : an overview. Journal for Labour Market Research 46, 185–199.

Azar, J., Marinescu, I., Steinbaum, M., Taska, B., 2020. Concentration in us labor markets: Evidence from online vacancy data. Labour Economics 66, 101886.

Bergeaud, A., Malgouyres, C., Mazet-Sonilhac, C., Signorelli, S., 2021. Technological change and domestic outsourcing .

Bhuller, M., Ferraro, D., Kostøl, A.R., Vigtel, T.C., 2023. The internet, search frictions and aggregate unemployment. Technical Report. National Bureau of Economic Research.

Bhuller, M., Kostol, A.R., Vigtel, T.C., 2020. How broadband internet affects labor market matching. Technical Report. IZA Discussion Papers.

Cambini, C., Grinza, E., Sabatino, L., 2023. Ultra-fast broadband access and productivity: Evidence from italian firms. International Journal of Industrial Organization 86, 102901.

Czernich, N., Falck, O., Kretschmer, T., Woessmann, L., 2011. Broadband infrastructure and economic growth. The Economic Journal 121, 505–532.

van Dam, A., Gomez-Lievano, A., Neffke, F., Frenken, K., 2023. An information-theoretic approach to the analysis of location and colocation patterns. Journal of Regional Science 63, 173–213.

Deming, D., Kahn, L.B., 2018. Skill requirements across firms and labor markets: Evidence from job postings for professionals. Journal of Labor Economics 36, S337–S369.

Denzer, M., Schank, T., Upward, R., 2021. Does the internet increase the job finding rate? evidence from a period of expansion in internet use. Information Economics and Policy 55, 100900.

Egli, F., Schmid, N., Schmidt, T.S., 2022. Backlash to fossil fuel phase-outs: The case of coal mining in us presidential elections. Environmental Research Letters 17, 094002.

Esco, 2022. Digital skills and knowledge concepts: Labelling the esco classification. European Commission .

Faberman, R.J., Kudlyak, M., et al., 2016. What does online job search tell us about the labor market. Economic perspectives 40, 1–15.

Fabling, R., Grimes, A., 2021. Picking up speed: Does ultrafast broadband increase firm productivity? Information Economics and Policy 57, 100937.

Gillett, S., Lehr, W., Osorio, C.A., Sirbu, M.A., 2006. Measuring the economic impact of broadband deployment. US Department of Commerce, Economic Development Administration .

Gürtzgen, N., Diegmann, A., Pohlan, L., van den Berg, G.J., 2021. Do digital information technologies help unemployed job seekers find a job? evidence from the broadband internet expansion in germany. European Economic Review 132, 103657.

Hershbein, B., Kahn, L.B., 2018. Do recessions accelerate routine-biased technological change? evidence from vacancy postings. American Economic Review 108, 1737–1772.

Kolko, J., 2012. Broadband and local growth. Journal of Urban Economics 71, 100–113.

Kruse, T., Dechezleprêtre, A., Saffar, R., Robert, L., 2022. Measuring environmental policy stringency in OECD countries: An update of the OECD composite EPS indicator. OECD Economics Department Working Papers 1703. OECD Publishing.

Kureková, L.M., Beblavỳ, M., Thum-Thysen, A., 2015. Using online vacancies and web surveys to analyse the labour market: A methodological inquiry. IZA Journal of Labor Economics 4, 1–20.

Lennon, C., Zilian, L.S., Zilian, S.S., 2023. Digitalisation of occupations—developing an indicator based on digital skill requirements. Plos one 18, e0278281.

Lovaglio, P.G., Cesarini, M., Mercorio, F., Mezzanzanica, M., 2018. Skills in demand for ict and statistical occupations: Evidence from web-based job vacancies. Statistical Analysis and Data Mining: The ASA Data Science Journal 11, 78–91.

Michaels, G., Natraj, A., Van Reenen, J., 2014. Has ict polarized skill demand? evidence from eleven countries over twenty-five years. Review of Economics and Statistics 96, 60–77.

Modestino, A.S., Shoag, D., Ballance, J., 2020. Upskilling: Do employers demand greater skill when workers are plentiful? Review of Economics and Statistics 102, 793–805.

Mueller, A.I., Osterwalder, D., Zweimüller, J., Kettemann, A., 2024. Vacancy durations and entry wages: Evidence from linked vacancy–employer–employee data. Review of Economic Studies 91, 1807–1841.

Point Topic, 2024. European broadband markets. Data set. Technical Report. Point Topic.

Samek, L., Squicciarini, M., Cammeraat, E., 2021. The human capital behind ai. OECD Science, Technology and Industry Policy Papers .

Squicciarini, M., Nachtigall, H., 2021. Demand for ai skills in jobs: Evidence from online job postings. OECD Science, Technology and Industry Working Papers 2021, 1–74.

Usabiaga, C., Núñez, F., Arendt, L., Gałecka-Burdziak, E., Pater, R., 2022. Skill requirements and labour polarisation: An association analysis based on polish online job offers. Economic Modelling 115, 105963.

Vuorikari, R., Jerzak, N., Karpinski, Z., Pokropek, A., Tudek, J., et al., 2022. Measuring digital skills across the eu: digital skills indicator 2.0. Joint Research Centre Publications Office of the European Union , 4–26.

Wooldridge, J.M., 2015. Control function methods in applied econometrics. Journal of Human Resources 50, 420–445.

Zilian, L.S., Zilian, S.S., Jäger, G., 2021. Labour market polarisation revisited: evidence from austrian vacancy data. Journal for labour market research 55, 7.

6 Appendix

6.1 The distributions of job posting variables.

The distributions of all job posting variables share certain features that bias the OLS estimates. To illustrate the point, we focus here on Total OJAs and OJAs with at least a digital skill. As shown in table 2, OJAs with at least a digital skill exhibits 30% of total observations equal to 0, meaning that no skills of the digital type are counted (informative zeros). For this reason, the model should account for the presence of informative zeros, which represent meaningful absences rather than missing data. Even if the variable Total OJAs has no zero values, both variables are heavily right-skewed, and the assumption of normality of residuals is violated (see figures 15 and 16 and table 1). In this case, OLS is not the best choice because it assumes a continuous, normally distributed outcome. We use, instead, models designed for discrete count data, such as Poisson estimation or Negative Binomial estimation, that are specifically tailored for count data and can better handle the skewness and non-normality of residuals.

Moreover, fixed effects enable us to control for unobserved heterogeneity at both the country and time levels, capturing region-specific, job-specific, and time-specific effects that may influence the dependent variables describing job postings. Table 1 also reveals the existence of over-dispersion in the dependent variables ($variance > mean$), suggesting that the Negative Binomial estimator would be preferable to the Poisson method, as it accounts for this excess variability. However, a key issue with the Negative Binomial model is that it automatically excludes groups where all observations are zero, resulting in a substantial loss of data if many groups contain only zeros. This can be particularly problematic if these dropped groups hold valuable information about the absence of specific skills in job postings. As a result, while Negative Binomial regression addresses over-dispersion, it may also significantly reduce the sample size. For this reason, in the paper we present results obtained using the Poisson method, whereas the estimates obtained under the Negative Binomial estimator are presented below for robustness.

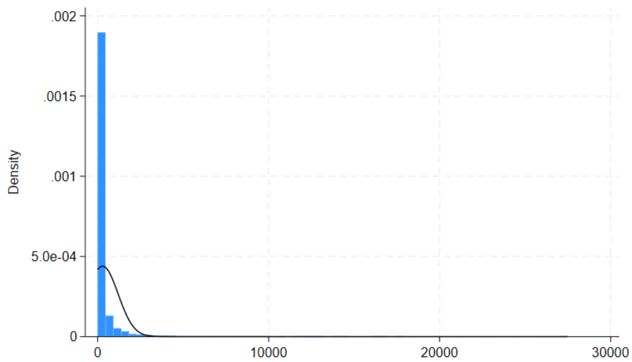
Table 1: Summary Statistics for OJAs and Digital OJAs

Variable	Observations	Mean	Std. Dev.	Min	Max	Skewness
`Digital OJAs`	12,971	106.70	538.10	0	25,829	18.06
`OJAs`	12,971	289.63	907.58	1	27,488	9.21

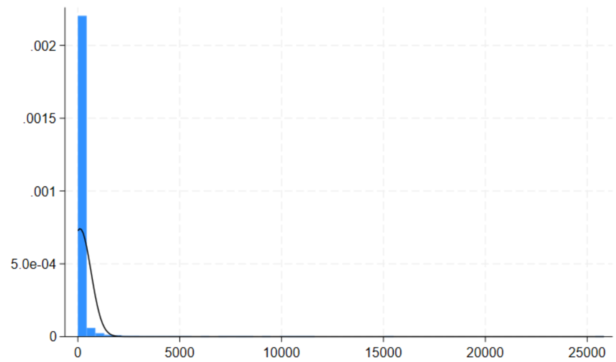
Table 2: Count of Zero Values in digital OJAs. Observations are aggregated at the Isco-3-digit code level

Condition	Count
`Digital OJAs = 0`	4,413

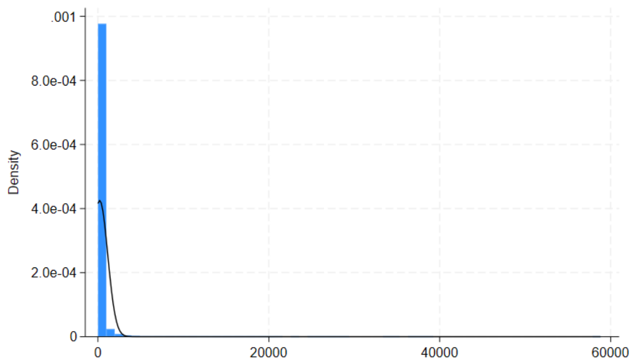
Figure 15: Variable distribution vs. normal



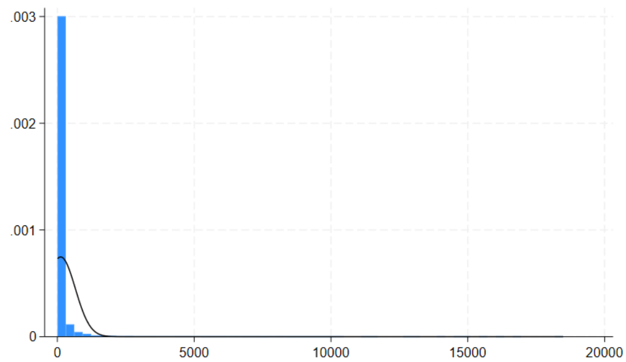
(a) OJAs aggregated at Isco-3 level



(b) digital OJAs aggregated at isco-3 level

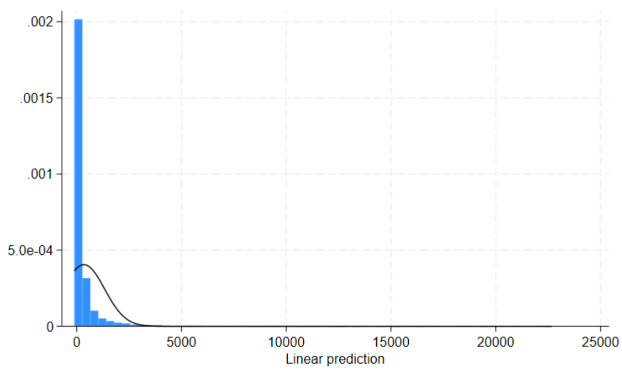


(c) OJAs aggregated at isco-4 level

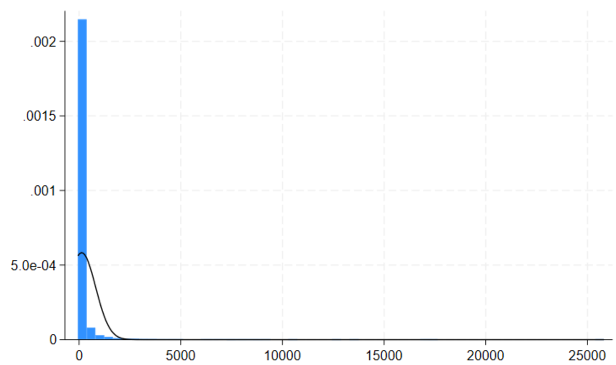


(d) digital OJAs aggregated at isco-4 level

Figure 16: Distribution of model residuals



(a) OJAs



(b) digital OJAs

6.2 Instrument test

Table 3: First-Stage Regression Test Results by speed for instrument 1

Test	Bandwidth	Value	P-Value	Threshold
Weak id. (Kleibergen-Paap Wald F)	30 Mbit/s	4.61	–	< 16.38 (10% size)
	100 Mbit/s	18.82	–	> 16.38 (10% size)
Anderson-Rubin Wald F-test	30 Mbit/s	7.37	0.0043	< 0.05 (Rejected)
	100 Mbit/s	131.68	0.0000	< 0.05 (Rejected)
Anderson-Rubin Chi-sq test	30 Mbit/s	15.53	0.0004	< 0.05 (Rejected)
	100 Mbit/s	138.62	0.0000	< 0.05 (Rejected)
Stock-Wright LM S test	30 Mbit/s	8.41	0.0149	< 0.05 (Rejected)
	100 Mbit/s	6.86	0.0088	< 0.05 (Rejected)

Table 4: First-Stage Regression Test Results by speed for instrument 2

Test	Bandwidth	Value	P-Value	Threshold
Weak id. (Kleibergen-Paap Wald F)	30 Mbit/s	3.01	–	< 16.38 (10% size)
	100 Mbit/s	19.10	–	> 16.38 (10% size)
Anderson-Rubin Wald F-test	30 Mbit/s	3.17	0.0637	> 0.05 (Not rejected)
	100 Mbit/s	89.77	0.0000	< 0.05 (Rejected)
Anderson-Rubin Chi-sq test	30 Mbit/s	6.66	0.0358	< 0.05 (Rejected)
	100 Mbit/s	94.50	0.0000	< 0.05 (Rejected)
Stock-Wright LM S test	30 Mbit/s	4.53	0.1040	> 0.05 (Not rejected)
	100 Mbit/s	10.03	0.0015	< 0.05 (Rejected)

6.3 First-stage regression tables

Table 5: First-Stage Regression: 30 Mbit/s broadband coverage on "nearest node"and 100Mbit/s broadband coverage on broadband exposure (Robust SEs, 4-digit ISCO classification)

	30 Mbit/s	100 Mbit/s
summed_instrument	$-8.94e-07^{***}$	
	(1.92e-07)	
broadband exposure		$1.89e-07^{***}$
		(3.39e-08)
2014	-0.6560^{***}	-0.4857^{***}
	(0.0260)	(0.0156)
2015	-0.5243^{***}	-0.4585^{***}
	(0.0258)	(0.0151)
2016	-0.3694^{***}	-0.4454^{***}
	(0.0284)	(0.0143)
2017	-0.1698^{***}	-0.4210^{***}
	(0.0214)	(0.0151)
2018	-0.0309^{**}	-0.3925^{***}
	(0.0123)	(0.0156)
2019	-0.0124^{***}	-0.3748^{***}
	(0.0040)	(0.0153)
constant	2.2415^{***}	0.3987^{***}
	(0.3248)	(0.0290)
Panel-level stats:		
σ_u	1.5643	0.2073
σ_e	0.0613	0.0329
ρ	0.9985	0.9755

Robust standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

6.4 Second-stage regression tables

Table 6: Effects of 30 Mbit/s and 100 Mbit/s broadband coverage on **total vacancies**

	30 Mbit/s (IV)	**100 Mbit/s (IV)**
L.depvar	-0.0000437	-0.0000401
	(0.0000349)	(0.0000354)
broadband	0.6136^{**}	0.9896^{***}
	(0.2800)	(0.2622)
L.broadband	0.2934^{***}	-0.0292
	(0.0895)	(0.2607)
broadband resid.	-0.5853^{**}	-0.9381^{***}
	(0.2915)	(0.3135)
constant	4.9810^{***}	5.0765^{***}
	(0.1990)	(0.1795)
Absorbed FE	Yes	
Time FE	Yes	
Observations	83,638	83,638

Standard/Bootstrap standard errors in parentheses. 4-digit ISCO classification

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 7: Effects of 30 Mbit/s and 100 Mbit/s broadband coverage on **digital vacancies**

	30 Mbit/s (No IV)	**100 Mbit/s (No IV)**
L.depvar	-0.0003209^{***}	-0.0003273^{***}
	(0.0000559)	(0.0000565)
broadband	0.2245^{*}	0.2987^{**}
	(0.1201)	(0.1462)
L.broadband	0.4019^{***}	-0.4103
	(0.1004)	(0.2547)
constant	5.0012^{***}	5.4116^{***}
	(0.0969)	(0.1015)
Absorbed FE	Yes	
Time FE	Yes	
Observations	71,219	71,219

Standard/Bootstrap standard errors in parentheses. 4-digit ISCO classification

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 8: Effects of 30 Mbit/s and 100 Mbit/s broadband diffusion on the **share of digital vacancies**

	30 Mbit/s (No IV)	**100 Mbit/s (IV)**
L.depvar	-0.2903^{***}	-0.2986^{***}
	(0.0092)	(0.0122)
broadband	0.0252	-0.1547
	(0.0412)	(0.1303)
L.broadband	-0.0068	0.5996^{***}
	(0.0353)	(0.1684)
broadband resid.	—	0.3852^{**}
		(0.1562)
constant	-0.2139^{***}	-0.0480
	(0.0289)	(0.0806)
Absorbed FE	Yes	
Time FE	Yes	
Observations	71,219	71,219

Standard/Bootstrap standard errors in parentheses. 4-digit ISCO classification

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 9: Effects of 30 Mbit/s and 100 Mbit/s broadband diffusion on the **variety of digital skills**

	30Mbit/s (IV)	100Mbit/s (IV)
L.depvar	-0.01495^{***}	-0.01508^{***}
	(0.00136)	(0.00144)
broadband	0.7239^{***}	0.7385^{***}
	(0.1303)	(0.1258)
L.broadband	0.1673^{***}	-0.4211^{***}
	(0.0444)	(0.1331)
broadband resid.	-0.7422^{***}	-0.5887^{***}
	(0.1265)	(0.1583)
constant	1.2977^{***}	1.6389^{***}
	(0.0876)	(0.0794)
Absorbed FE	Yes	
Time FE	Yes	
Observations	71,219	71,219

Standard/Bootstrap standard errors in parentheses. 4-digit ISCO classification

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 10: Effects of 30 Mbit/s and 100 Mbit/s broadband diffusion on the **digital skill dispersion ratio**

	30 Mbit/s (No IV)	100 Mbit/s (No IV)
L.depvar	-0.2135^{***}	-0.191^{***}
	(0.0113)	(0.0187)
broadband	-0.1281^{**}	0.159
	(0.0524)	(0.130)
L.broadband	0.0524	-0.0948
	(0.0452)	(0.374)
constant	-1.0213^{***}	-1.060^{***}
	(0.0413)	(0.114)
Absorbed FE	Yes	
Time FE	Yes	
Observations	45,419	30,979

Standard/Bootstrap standard errors in parentheses. 4-digit ISCO classification

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 11: Effects of 30 Mbit/s and 100 Mbit/s broadband on **cognitive vacancies**

	30 Mbit/s (No IV)	**100 Mbit/s (No IV)**
L.depvar	−0.00041***	−0.00041***
	(–3.96)	(–3.96)
broadband	0.3280**	0.6159***
	(2.27)	(3.64)
L.broadband	0.5962***	−0.9946***
	(5.05)	(–3.10)
constant	4.4069***	5.0116***
	(38.28)	(41.33)
Absorbed FE	Yes	
Time FE	Yes	
Observations	61,335	61,335

Standard/Bootstrap standard errors in parentheses. 4-digit ISCO classification

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 12: Effects of 30 Mbit/s and 100 Mbit/s broadband diffusion on the **share of cognitive vacancies**

	30 Mbit/s (No IV)	**100 Mbit/s (No IV)**
L.depvar	−0.3899***	−0.3899***
	(0.0137)	(0.0137)
broadband	−0.0079	0.0996
	(0.0694)	(0.0842)
L.broadband	0.1484**	−0.0142
	(0.0588)	(0.1816)
constant	−0.5861***	−0.5358***
	(0.0482)	(0.0576)
Absorbed FE	Yes	
Time FE	Yes	
Observations	61,335	61,335

Standard/Bootstrap standard errors in parentheses. 4-digit ISCO classification

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 13: Effects of 30 Mbit/s and 100 Mbit/s broadband diffusion on the **variety of cognitive skills**

	30 Mbit/s (IV)	100 Mbit/s (IV)
L.depvar	-0.0435^{***}	-0.0439^{***}
	(0.0022)	(0.0021)
broadband	1.1496^{***}	0.9143^{***}
	(0.1579)	(0.1492)
L.broadband	0.2879^{***}	-0.5911^{***}
	(0.0589)	(0.1674)
broadband resid.	-1.1760^{***}	-0.6652^{***}
	(0.1525)	(0.1850)
constant	0.7783^{***}	1.4736^{***}
	(0.1081)	(0.0927)
Absorbed FE	Yes	
Time FE	Yes	
Observations	61,335	61,335

Standard/Bootstrap standard errors in parentheses. 4-digit ISCO classification
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 14: Effects of 30 Mbit/s and 100 Mbit/s broadband diffusion on the **cognitive skill dispersion ratio**

	30 Mbit/s (No IV)	100 Mbit/s (No IV)
L.depvar	-0.1956^{***}	-0.1948^{***}
	(0.0130)	(0.0130)
broadband	-0.1993^{***}	-0.1747^{*}
	(0.0629)	(0.1051)
L.broadband	-0.0992^{*}	0.0297
	(0.0551)	(0.1892)
constant	-0.7336^{***}	-0.8635^{***}
	(0.0499)	(0.0658)
Absorbed FE	Yes	
Time FE	Yes	
Observations	28,722	28,722
Pseudo R^2	0.1240	0.1240

Standard/Bootstrap standard errors in parentheses. 4-digit ISCO classification
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

6.5 Labour-market variables - Regression tables

Table 15: Impact of a 1% increase in broadband diffusion on employment and unemployment (no IV estimates)

	Employment (30 Mbit/s)	**Employment (100 Mbit/s)**	**Unemployment (30 Mbit/s)**	**Unemployment (100 Mbit/s)**
L.depvar	0.8814***	0.8755***	0.2806**	0.2919**
	(0.0624)	(0.0637)	(0.1023)	(0.1026)
broadband	0.0093	−0.0013	−0.0062	−0.0116
	(0.0104)	(0.0232)	(0.0086)	(0.0189)
L.broadband	−0.0183*	0.0028	−0.0045	0.0175
	(0.0097)	(0.0380)	(0.0080)	(0.0308)
Constant	0.7935*	0.8258*	0.0809***	0.0751***
	(0.4112)	(0.4215)	(0.0133)	(0.0138)
Observations	126			
Within R^2	0.8765	0.8719	0.7320	0.7293

Robust standard errors in parentheses.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

6.6 Digital occupations - Regression Tables

Table 16: Effects of 30 Mbit/s and 100 Mbit/s broadband coverage on **total vacancies**, interacted with the Relative Comparative Advantage (RCA) index (discretized).

	30 Mbit/s (IV)	**100 Mbit/s (IV)**
L. depvar	−0.00004	−0.00004
	(0.00003)	(0.00004)
broadband	0.5937**	0.8634***
	(0.2828)	(0.2543)
broadband × RCA	0.0125	0.2788***
	(0.1191)	(0.0706)
L.broadband	0.3460***	0.7232***
	(0.1033)	(0.2702)
L.broadband × RCA	−0.1252	−1.5315***
	(0.0978)	(0.2653)
broadband resid.	−0.5751**	−0.9563***
	(0.2867)	(0.3035)
constant	4.9977***	5.0724***
	(0.1926)	(0.1757)
Absorbed FE	Yes	
Time FE	Yes	
Observations	83,638	83,638

Standard/Bootstrap standard errors in parentheses. 4-digit ISCO classification

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 17: Effects of 30 Mbit/s and 100 Mbit/s broadband coverage on **digital vacancies**, interacted with RCA (discretized).

	30 Mbit/s (IV)	**100 Mbit/s (IV)**	**100 Mbit/s (No IV)**
L. depvar	-0.00035^{***}	-0.00033^{***}	-0.00032^{***}
	(0.00007)	(0.00007)	(0.00006)
broadband	-0.6652^{*}	-0.0743	0.1378
	(0.3614)	(0.3434)	(0.1484)
broadband × RCA	0.1396	0.2508^{***}	0.2507^{***}
	(0.1515)	(0.0866)	(0.0645)
L.broadband	0.6404^{***}	0.4120	0.4318
	(0.1545)	(0.3481)	(0.2761)
L.broadband × RCA	-0.1514	-1.2632^{***}	-1.2716^{***}
	(0.1265)	(0.2939)	(0.2426)
broadband resid.	0.8267^{**}	0.4163	—
	(0.3924)	(0.3784)	
constant	5.5165^{***}	5.5431^{***}	5.4071^{***}
	(0.2387)	(0.2255)	(0.1005)
Absorbed FE		Yes	
Time FE		Yes	
Observations	71,219	71,219	71,219

Standard/Bootstrap standard errors in parentheses. 4-digit ISCO classification

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 18: Effects of 30 Mbit/s and 100 Mbit/s broadband coverage on the **share of digital vacancies**, interacted with the Relative Comparative Advantage (RCA) index (discretized).

	30 Mbit/s (IV)	**100 Mbit/s (IV)**
L. depvar	-0.0001^{***}	-0.0001^{***}
	(0.00002)	(0.00002)
broadband	-0.2126	-0.2823
	(0.5171)	(0.4693)
broadband × RCA	-0.0136	0.5810^{***}
	(0.1926)	(0.1103)
L.broadband	0.8001^{***}	0.2719
	(0.2150)	(0.5002)
L.broadband × RCA	-0.0209	-2.3602^{***}
	(0.1600)	(0.4062)
broadband resid.	0.8726^{*}	1.1734^{**}
	(0.5279)	(0.5186)
constant	6.5563^{***}	7.3112^{***}
	(0.3496)	(0.3286)
Absorbed FE	Yes	
Time FE	Yes	
Observations	71,219	71,219

Standard/Bootstrap standard errors in parentheses. 4-digit ISCO classification

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 19: Effects of 30 Mbit/s and 100 Mbit/s broadband diffusion on the **variety of digital skills**, interacted with the Relative Comparative Advantage (RCA) index (discretized).

	30 Mbit/s (IV)	**100 Mbit/s (IV)**
L. depvar	-0.0145^{***}	-0.0152^{***}
	(0.0014)	(0.0014)
broadband	0.6155^{***}	0.6245^{***}
	(0.1367)	(0.1267)
broadband × RCA	0.1631^{**}	0.1660^{***}
	(0.0630)	(0.0331)
L.broadband	0.2769^{***}	0.0916
	(0.0528)	(0.1496)
L.broadband × RCA	-0.1607^{***}	-0.7522^{***}
	(0.0500)	(0.1279)
broadband resid.	-0.7464^{***}	-0.5851^{***}
	(0.1310)	(0.1582)
constant	1.2922^{***}	1.6385^{***}
	(0.0891)	(0.0802)
Absorbed FE	Yes	
Time FE	Yes	
Observations	71,219	71,219

Standard/Bootstrap standard errors in parentheses. 4-digit ISCO classification
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 20: Effects of 30 Mbit/s and 100 Mbit/s broadband diffusion on the **digital skill dispersion ratio**, interacted with the Relative Comparative Advantage (RCA) index (discretized).

	30 Mbit/s (IV)	100 Mbit/s (IV)
L. depvar	−0.2140***	−0.2136***
	(0.0151)	(0.0151)
broadband	0.3011	−0.3618
	(0.2555)	(0.2861)
broadband × RCA	−0.0247	−0.0817
	(0.0884)	(0.0616)
L.broadband	0.0591	−0.0364
	(0.0745)	(0.2585)
L.broadband × RCA	−0.0578	−0.1510
	(0.0718)	(0.2307)
broadband resid.	−0.4316*	0.3310
	(0.2559)	(0.3060)
constant	−1.3193***	−0.8196***
	(0.1781)	(0.1709)
Absorbed FE	Yes	
Time FE	Yes	
Observations	45,419	45,419

Standard/Bootstrap standard errors in parentheses. 4-digit ISCO classification

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 21: Effects of 30 Mbit/s and 100 Mbit/s broadband coverage on **cognitive vacancies**, interacted with RCA (discretized).

	30 Mbit/s (IV)	**100 Mbit/s (IV)**
L. depvar	-0.00045^{***}	-0.00044^{***}
	(0.00015)	(0.00015)
broadband	-0.2982	0.0790
	(0.4547)	(0.4043)
broadband × RCA	0.1743	0.4815^{***}
	(0.1934)	(0.1060)
L.broadband	0.7017^{***}	-0.1588
	(0.1863)	(0.4405)
L.broadband × RCA	-0.0229	-1.3405^{***}
	(0.1584)	(0.3794)
broadband resid.	0.5382	0.4367
	(0.4816)	(0.4660)
constant	4.7482^{***}	5.1668^{***}
	(0.2997)	(0.2787)
Absorbed FE	Yes	
Time FE	Yes	
Observations	61,335	61,335

Standard/Bootstrap standard errors in parentheses. 4-digit ISCO classification

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 22: Effects of 30 Mbit/s and 100 Mbit/s broadband coverage on the **share of cognitive vacancies**, interacted with RCA (discretized).

	30 Mbit/s (IV)	**100 Mbit/s (IV)**
L. depvar	-0.0434^{***}	-0.0443^{***}
	(0.0022)	(0.0022)
broadband	1.1225^{***}	0.7666^{***}
	(0.1622)	(0.1413)
broadband × RCA	0.0507	0.2471^{***}
	(0.0883)	(0.0417)
L.broadband	0.3146^{***}	−0.1671
	(0.0673)	(0.1945)
L.broadband × RCA	−0.0480	-0.7586^{***}
	(0.0679)	(0.1664)
broadband resid.	-1.1772^{***}	-0.6562^{***}
	(0.1495)	(0.1789)
constant	0.7771^{***}	1.4806^{***}
	(0.1048)	(0.0905)
Absorbed FE	Yes	
Time FE	Yes	
Observations	61,335	61,335

Standard/Bootstrap standard errors in parentheses. 4-digit ISCO classification

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 23: Effects of 100 Mbit/s broadband coverage on the **cognitive skill variety**, interacted with RCA (discretized).

	30 Mbit/s (IV)	100 Mbit/s (IV)
L. depvar	-0.0425^{***}	-0.0428^{***}
	(0.0022)	(0.0022)
broadband	1.0403^{***}	0.9544^{***}
	(0.1684)	(0.1546)
broadband × RCA	0.2405^{***}	-0.0798^{**}
	(0.0866)	(0.0405)
L.broadband	0.4752^{***}	-0.0480
	(0.0640)	(0.1889)
L.broadband × RCA	-0.4190^{***}	-1.1125^{***}
	(0.0683)	(0.1596)
broadband resid.	-1.1816^{***}	-0.6763^{***}
	(0.1547)	(0.1931)
constant	0.7773^{***}	1.4616^{***}
	(0.1101)	(0.0978)
Absorbed FE	Yes	
Time FE	Yes	
Observations	61,335	61,335

Bootstrap standard errors in parentheses. 4-digit ISCO classification

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 24: Effects of 30 Mbit/s and 100 Mbit/s broadband coverage on the **cognitive skill dispersion ratio**, interacted with RCA (discretized).

	30 Mbit/s (no IV)	**100 Mbit/s (no IV)**
L. depvar	-0.1960^{***}	-0.1952^{***}
	(0.0130)	(0.0130)
broadband	-0.2035^{***}	-0.1359
	(0.0728)	(0.1073)
broadband × RCA	0.0067	-0.0860^{*}
	(0.0854)	(0.0518)
L.broadband	-0.0732	0.0056
	(0.0620)	(0.2101)
L.broadband × RCA	-0.0592	0.0584
	(0.0689)	(0.2009)
constant	-0.7330^{***}	-0.8647^{***}
	(0.0499)	(0.0658)
Absorbed FE	Yes	
Time FE	Yes	
Observations	28,722	

Robust standard errors in parentheses. 4-digit ISCO classification.

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$