ICTs and the Urban-Rural Divide: Can Online Labour Platforms Bridge the Gap?

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ABSTRACT
Information and communication technologies have long been predicted to make cities as hubs of economic organisation obsolete and spread economic opportunities to rural areas. However, the actual trend in the 21st century has been the opposite. Knowledge spillovers have fuelled urbanisation and pulled job-seekers into large cities, increasing the gap to deprived rural areas. We argue that new assemblages of technologies and social practices, so-called 'online labour platforms', have recently started to counter this trend. By providing effective formal and informal mechanisms of enforcing cooperation, these platforms for project-based remote knowledge work enable users to hire and find work across distance. In analysing data from a leading online labour platform in more than 3,000 urban and rural counties in the United States, we find that rural workers made disproportionate use of the online labour market. Rural counties also supplied, on average, higher skilled online work than urban areas did. However, many of the most deprived regions of the country did not participate in the online labour market at all. Our findings highlight the potentials and limitations of such platforms for regional economic development.

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Information and Communication Technology • Platform Economy • Online Labour Platforms • Urban-Rural Divide • Spatial Inequality • Regional Development

1. Introduction

Digital technologies enabled online marketplaces, created new industries, and started to fundamentally change many parts of the economy (Mayer-Schönberger and Ramge, 2018). This trend has fuelled urbanisation, as large metropolitan areas emerged as clusters of knowledge intensive industries providing highly paid, creative jobs (Clark, Feldman, Gertler, and Wójcik, 2018; Florida and Mellander, 2018; Forman, Goldfarb, and Greenstein, 2018). These jobs pulled educated workers into the large cities, sparking more knowledge spillovers that increased the gap between thriving urban centres and deprived rural areas. So far, the Internet has failed to turn the world into a 'spaceless city' (Pawley, 1995).

However, new assemblages of technologies and social practices, so-called 'online labour platforms', have recently started to re-imagine the entire hiring and work process, by enabling

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workers and employers to conclude contracts and enforce cooperation across distance. As their use is growing rapidly (Kässi and Lehdonvirta, 2018b; Kuek, Paradi-Guilford, Fayomi, Imaizumi, Ipeirotis, Pina, and Singh, 2015; Manyika, Lund, Robinson, Valentino, and Dobbs, 2015), we ask whether these platforms finally alleviate the urban-rural divide in bringing economic opportunities to rural areas?

So far, research on the geography of online labour markets focused on the country level (Horton, Kerr, and Stanton, 2017; Kässi and Lehdonvirta, 2018b), or on frictions affecting the international service trade on these platforms (Beerepoot and Lambregts, 2015; Ghani, Kerr, and Stanton, 2014; Hong and Pavlou, 2014). Urban-rural differences in the use of online labour platforms remain poorly understood.

We therefore examine sub-national differences in online labour supply between urban and rural areas to evaluate whether such platforms have helped rural workers to find work online. To achieve this, we match geocoded transactions data from a leading online labour platform with data from the U. S. county-level labour market statistics. The findings suggest that online labour platforms disproportionately benefit skilled workers in rural areas.

2. Background: The Tenacity of Distance

Information and communication technologies (ICTs) have long been predicted to make cities as hubs of economic organisation obsolete (Cairncross, 1997; Gaspar and Glaeser, 1998; Graham, 1998). This is because 'all persons tapped into the global communications network [...] have ties approximating those used in a given metropolitan region' (Webber, 1968, p. 1096). As a result, 'What once had to happen in the city can now take place anywhere' (Pascal, 1987, p. 602). This includes work and business: 'the Internet creates a "borderless" virtual business platform on which suppliers, customers, competitors and network partners can freely interact [and] by-pass the traditional interaction patterns' (Poon and Jevons, 1997, p. 34). As ICTs proliferate, 'it is no longer necessary to leave your home to work' (Morgan and Smit, 1996, p. 136).

These predictions presume that ICTs function as near-perfect substitutes to proximate interactions: that they provide 'all the richness and subtlety of the immersive communications once available only through place-based interactions in urban areas' (Graham, 1998, p. 169). The 'Information Superhighway' makes actual highways unnecessary (Sawhney, 1996) and turns the world into a 'global village' (McLuhan, 1964). Every area, no matter how rural, is integrated into a 'spaceless city' where 'the whole population might require no more than the 30 atom diameter light beam of an optical computer system' (Pawley, 1995). According to Graham (1998, p. 168), 'the "logic" of telecommunications and electronic mediation is therefore interpreted as inevitably supporting geographical dispersal from large metropolitan regions, or even the effective dissolution of the city itself'.

The rising 'knowledge economy' discourse (Drucker, 1969) fuelled these predictions: knowledge processing contributed increasingly to the economic value produced by firms and countries, diminishing the relative economic importance of the manipulation and transportation of physical matter. Thus, even if physical capital, labour, and products could never be carried by the Information Superhighway, 'Informational labour' — the accumulation, manipulation, and dissemination of various forms of information — would become the most important segment of the labour market (Castells, 1998). As its' outputs are mediated by digital communication networks, the economy would increasingly be shaped by digital 'bits', rather than geographically bound 'atoms' (Negroponte, 1995).

Although ICTs undeniably affected massively the organisation of economic activities, they have not made cities obsolete. Urbanisation remains a megatrend in the 21st century that accelerated in recent years (Clark et al., 2018; Glaeser, Kolko, and Saiz, 2001). Currently, more than half the world population lives in cities, and this proportion will rise to more than two-thirds by 2050 (UN, 2018). In North America, already four out of five people gather in urban areas. People flock to urban centres in search of jobs and other opportunities. The downside is congested cities and increasingly deprived rural areas (Glasmeier, 2018). Against the face of massive ICT-adoption, the effects of distance remain surprisingly tenacious. To emulate Robert Solow, 'you can see the information age everywhere but on the map'.

What explains this 'urbanisation paradox'? Short distances in cities allow ideas to move easily, making them hotbeds of innovation and business opportunities (Florida and Mellander, 2018; Glaeser and Kahn, 2004). The 'death of distance' (Cairncross, 1997) literature predicted that ICTs would eliminate the urban advantage by allowing information to flow anywhere with equal ease. In practice, they rarely offered 'all the richness and subtlety' (Graham, 1998, p. 169) of proximate interaction. Online job adverts replaced newspaper advertisements, but hiring processes retained location-specific parts like face-to-face interviews. In the United States, broadband Internet connectivity only recently obtained a good coverage in rural areas (Horrigan, 2010), and 'Digital Divides' in ICT-access and use reproduced spatial inequalities (Gilbert, 2010; Howard, Busch, and Sheets, 2010; Philip and Williams, 2018; Riddlesden and Singleton, 2014; Strover, 2014).

We argue that information flows alone are not sufficient to trigger the spatial reorganisation of economic activity. Economic sociology and economic history emphasise that to function effectively, job markets and firms need 'systems of control': means of enforcing cooperation and combating opportunism (Granovetter, 2005; Ogilvie, 2011). Workers need to be reasonably sure that they will get paid, and employers need to be reasonably sure that they get the labour they are paying for. Both can be secured either by formal mechanisms of monitoring and sanctioning, such as contracts and courts (North, 1990), or by embedding economic activities in informal social networks that provide trust and social control (Granovetter, 1985). Without any control mechanisms, economic activity is unlikely to arise at all.

Formal and informal control mechanisms are available in proximate transactions, but not necessarily in ICT-mediated transactions. If distant clients fail to pay, they may be difficult to take to court as they may be unidentifiable or belong to a different jurisdiction. Distant parties are also unlikely to belong to the same social networks and may adhere to different cultural norms, making informal enforcement of cooperation equally difficult. Consequently, although ICTs enhanced information flows enabling telecommuting and virtual teamwork, this did not result in job vacancies being filled over distance. People still needed to move to cities to look for work. In line with this argument, research suggests that cities have benefited disproportionately more than rural areas from reduced communication and search costs associated with the Internet (Forman et al., 2018; Kok and Weel, 2014), and that digital platforms reinforced the importance of spatial proximity and cities (Baker and Ward, 2002; Davidson and Poor, 2018; Mollick, 2014; Verboord and Noord, 2016).

However, a new wave of technologies and digitally mediated social practices could finally diminish the urban advantage to some extent. Online labour platforms are web-applications that mediate between buyers and sellers of remotely deliverable informational labour, such as software development, graphic design, and data entry (Horton, 2010). A World Bank study estimates that such platforms had annual turnovers of $ 4.8 billion in 2016, which may grow to $ 15 – $ 25 billion by 2020 (Kuek et al., 2015). Although these figures remain small compared to overall labour markets, the market has grown approximately 26 % over two years (Kässi and Lehdonvirta, 2018b); a rapid growth rate for a labour market.

Besides allowing parties to find each other and communicate, online labour platforms provide diverse mechanisms for enforcing cooperation, most notably reputation, escrow, remote monitoring, and online dispute resolution systems (Pallais, 2014; Pallais and Sands, 2016; Pelletier and Thomas, 2018; Wood, Graham, Lehdonvirta, and Hjorth, 2018a). Both workers and employers can perform 'due diligence' checks on each other based on platform-verified and platform-generated signals that are not merely a 'cheap talk' (Lehdonvirta, Kässi, Hjorth, Barnard, and Graham, 2018). Many users also use associated online forums and networks to exchange information about bad actors and to promulgate informal norms of good conduct (Lehdonvirta, 2016; Shevchuk and Strebkov, 2018; Wood, Lehdonvirta, and Graham, 2018b). Although these new ICT-mediated systems of control are by no means perfect (Agrawal, Lacetera, and Lyons, 2016; Lehdonvirta et al., 2018), they seem good enough to enable users to hire and find work across vast geographic distances.

Previous research has not investigated whether these non-proximate systems of control had implications to urban-rural divides. To our knowledge, only one study (Borchert, Hirth, Kummer, Laitenberger, Slivko, and Viete, 2018) focuses on the effect of local economic factors on the economic geography of online labour markets. The purpose of this paper is therefore to examine whether online labour platforms helped to finally deliver on ICTs' promise to alleviate the "tyranny of distances" (Virilio, 1993, p. 10) in extending economic opportunities to rural areas (Manyika et al., 2015).

3. Hypotheses

Urban areas offer more employment opportunities than rural areas, pulling job-seekers towards cities (Glasmeier, 2018; Greenwood, 1997; Lucas, 2004). Online labour platforms offer an alternative to such employment-based migration, constituting a form of 'virtual migration' (Ipeirotis and Horton, 2011). Accordingly, rural workers should have more incentives to use these platforms to find work than individuals in urban areas, where employment opportunities are widespread. This is captured by our first hypothesis:

H1: Rural areas supply more online labour proportional to population than urban areas do.

Cities do not online provide more employment opportunities, but they can also support more specialised jobs and larger occupational diversity (Bettencourt, Samaniego, and Youn, 2014; Quigley, 1998; Sveikauskas, 1975). Productivity gains from learning drive further specialisation, allowing skilled specialists to command higher wages. In rural areas, however, employers are sparse, and highly skilled workers will find it difficult to secure enough specialised work in their narrow domain. They will either have to look for more generalist, less well remunerated tasks or they have to migrate to cities. If online labour platforms alleviate geographic constraints on job search, then this should disproportionately benefit rural specialists, as they can access specialised demand beyond their local areas. Because urban areas provide specialised education to more people than rural areas, we need to take a county's general educational level into account, when comparing urban-rural difference in specialised online labour supply. Our second hypothesis is therefore:

H2: Rural areas supply higher skilled online labour relative to their general education level than urban areas do.

4. Materials and Methods

To examine the hypotheses, we construct novel measures of skill-specific online labour supply in the United States. We then provide descriptive and inferential statistics to compare online labour supply in urban and rural counties in the presence of appropriate socio-economic control variables.

4.1. Data Sources

The online labour dataset consists of all transactions carried out on a leading online labour platform between 1 March 2013 and 31 August 2013. It comprises 362,989 projects and includes each project's job category (34 possible categories) and the worker's location on a zip-code level.[1]

To ensure that the findings speak to urban-rural differences, we limit ourselves to projects where the freelancers are located in the United States. The analysis hinges on county- and occupation-level data available from the U. S. Census Bureau and the Bureau of Labour Statistics. Sub-national and occupational data are available from statistical agencies in other countries as well, but their levels of aggregation vary, and cross-national comparability is not straightforward. Moreover, we need to analyse the geographic distribution on the county-level for which Internet connectivity data are not available. The high broadband availability in the United States (Horrigan, 2010), however, makes this less of an issue.

To aggregate the platform data to the county-level used in official U.S. statistics, we use the *Google Geocoding API* and polygonal shapefiles published by the U. S. Census Bureau.[2] Filtering leaves us with 34,198 projects in 3,052 counties in the 48 contiguous U. S. states.

we employ the U.S. Office of Management and Budget classification system to opera-

[1] Details in (Lehdonvirta et al., 2018).
[2] `https://www.census.gov/geo/maps-data/data/cbf/cbf_description.html`

tionalise the urban-rural distinction. It assigns each county into either a rural, micropolitan, or metropolitan area, focusing on population concentration rather than on population numbers, which is in line with economic theorising on geographic concentration. A metropolitan area is defined as a core urban agglomeration of 50,000 or more population, while a micropolitan area has an urban core of at least 10,000, but less than 50,000, population. All other areas are rural. Counties can belong to a metropolitan area without itself having 50,000 inhabitants, if they are part of a larger urban agglomeration. Other counties can be classified as rural with a population in excess of 10,000, if they lack any urban core.

4.2. Determining the online labour skill level

For the second hypothesis, we need to assess the required skill level of the online labour projects. To do so, we aggregate the skill requirements into one numerical score per occupation in mapping the platform's project categorisation system to the Standard Occupation Classification (SOC) system, used by the U. S. Bureau of Labour Statistics. The method is not perfect as it ignores varying skill requirements of projects within one category and it equates educational qualification to skills, but it yields a common measure that provides comparability to the overall education level of a county.

For the mapping, we use the 'SOCcer' tool (Russ, Ho, Colt, Armenti, Baris, Chow, Davis, Johnson, Purdue, and Karagas, 2016), an online application developed by the National Institutes of Health to matche free-text job information to SOC-2010 occupation codes (Fig. 1A). As the 2013 transactions data do not include all project details, we needed to collect an additional dataset for the mapping. In January 2016, we drew a random sample of 345,000 transactions histories from 46,791 freelancers using the platform's application programming interface.[3] This dataset includes each project's category, title, skill requirements (indicated by the employer), and a free-text description (element 1. in Fig. 1A). Each project is fed into the SOCcer classifier, yielding the 10 most likely SOC codes (element 2.). The results of each category are manually inspected to warrant a reasonable matching (element 3.). If the highest scoring occupation did not provide a meaningful match, the results' list was searched for the next reasonable occupation and its' SOC definition was compared to a number of project descriptions per category to ensure reliability.[4]

Figure 1 near here.

For examples, the classifier assigned 88 % of the 'data entry' projects to 'Data Entry Keyers' (SOC-code 43-9021); an obviously good fit. Similarly, it assigned 75 % of the 'illustration' projects to 'Illustrators' (SOC-code 27-1013). In contrast, only 37 % of the 'web development' projects were assigned to 'Computer and System Managers', while 35 % were classified as 'Web Developers'. This result reflects the variation in the project descriptions and the similarity of the suggested occupations. Web Developers are categorised as '15-0000 Computer and Mathematical Occupations', which better fits to the projects' descriptions than 'Computer

[3]Details in (Kässi and Lehdonvirta, 2018a).
[4]`https://www.bls.gov/soc/soc_2010_definitions.pdf`

and Systems Managers' ('11-0000 Management Occupations'). Accordingly, we assigned 'web development' projects to 'Web Developers' (SOC-code 15-1134). In total, we mapped all 83 online job categories to 34 SOC occupations.

This mapping allowed us to calculate the required educational level of each occupation, using the occupation specific educational attainment statistics from the Bureau of Labour Statistics (Fig. 1B shows three examples).[5] To obtain one numerical score from the distributions, we calculated a weighted average in multiplying the proportion of workers in each educational level by Likert scale values. For example: 3 % of the Data Entry Keyers have no high school diploma (1), 26 % have one (2), 33 % have some college education (3), 14 % have an Associate's degree (4), 20 % have a Bachelor's degree (5), 4 % a Master's degree (6), and 1 % a Doctoral degree (7). Accordingly, the overall score of Data Entry Keyers is 48. Equivalently, the scores of Illustrators and Web Deveopers are 60 and 65, respectively. The resulting score only roughly approximates the educational variety of different occupations, but it yields one common scale to compare skill levels of different online jobs, which we need to examine $H2$.

The resulting scores of all 34 occupations vary substantially between the occupational groups (Fig. 1C). For example, the median score of 'Office and Administrative Support' is 48, while it is 65 for 'Computer and Mathematical'. The figure shows that all online jobs correspond to occupations that have been identified as 'outsourcable' (Blinder, 2009): the occupations are defined by tasks that do not require the physical presence at a certain location.

We average the scores of all projects in a county to obtain a measure of the relative online skill level of a county's online workforce. To account for heterogeneity in the educational attainment distribution across counties, we weight the online skill variable by a numerical education score of the county's overall population, which we have calculated in the same fashion as the online skill score. This yields a ratio: values larger (smaller) than one imply that the jobs conducted by the online workforce in a county was of higher (lower) educational level than the average educational level of the county's population.

4.3. Data Analysis

We applied multivariate analyses to investigate both research hypotheses. The number of projects per county ($H1$), represents non-normally distributed count data. This requires to apply an appropriate model specification such as the Poisson generalised linear model (GLM), instead of Ordinary Least Squares (OLS). Due to over-dispersion (the variance is much larger than the mean and many counties have no online projects, see the statistically significant estimators of the dispersion parameter θ in Tab. 3), the negative binomial regression, or the zero-inflated negative binomial regression represent even better suited model specifications (Zeileis, Kleiber, and Jackman, 2008).

In Tab. 3A, we report the regression results of all four model specifications and present the log Likelihood and the Akaike information criterion as in-sample goodness-of-fit measures.[6] Additionally, we assess the out-of-sample goodness-of-fit by a ten-fold cross validation and by

[5] `https://www.bls.gov/emp/tables/educational-attainment.htm`

[6] The parameter estimates and standard deviations displayed in the table are calculated from the complete dataset.

the mean absolute error and the Pearson correlation coefficient ρ between the predicted values and the test data (Tab. 3A, and Fig. 3 B and C). The purpose of reporting cross-validated results in this study is to increase the confidence in the research findings we report by assessing the robustness to outliers, to validate the model choice, and to estimate the prediction accuracy on unseen data (Janeksela, 1982). We report the significance of each parameter estimate in the ten cross-validation regressions on re-sampled data as coloured bars of different length in the 'CV signif.' labelled columns (Quattrone, Greatorex, Quercia, Capra, and Musolesi, 2018). The relative online education/skill score ($H2$), is normally distributed (Fig. 2C). Accordingly, ordinary least squares provides an appropriate model specification.

To test for spatial autocorrelation (spatial error), we report Moran's I measure of spatial autocorrelation (Moran, 1950) and Monte Carlo simulated p-values.[7]

As controls, we have collected socio-economic data from the U. S. Census Bureau American Community Survey (US-Census, 2016). For the variable selection, we oriented us at other studies that analyse the geography of online platforms: as characteristics of the local economy and the local labour market we have selected the median commuting time in minutes, the log-10 number of firms per capita, the unemployment rate and the log-10 median household income in USD (Borchert et al., 2018). Demographics are captured by the log-10 county population size and by a score measuring the educational level of county's population (Graham, Straumann, and Hogan, 2015). Moreover, we have included indicator variables for rural and micropolitan counties, and for spatial adjacency to a metropolitan area.

5. Results

Substantial urban-rural differences characterise the online labour market in the United States (Fig. 2). Metropolitan counties supply more online labour in absolute numbers, but rural areas supply more relative to their population (Tab. 2A, Fig. 2B); a finding that supports $H1$.

Figure 2 near here.

In line with $H2$, we find that rural areas provide relatively higher skilled online labour than urban areas (Fig. 2C). The average skill level of online labour supplied from rural areas is even slightly higher in absolute terms (Tab. 2A), despite notably higher average educational levels in urban areas (Fig. 2E).

These regional differences are associated with disparities in local income and economic opportunities between urban and rural areas (Tab. 2A, Fig. 2D). Additionally, we find that the vast majority of online labour demand is clustered in urban centres, which is in line with our theoretical framework.

Table 3A shows that the differences in online labour market participation between rural and

[7] Moran's I is a correlation coefficient showing the similarity between neighbouring values (in our case the regression residuals of neighbouring counties). Values close to +1 (−1) indicate a clustering of similar (dissimilar) values, while values close to zero indicate that spatial autocorrelation is not prevalent. In order to assess its significance, 1,000 Monte Carlos simulations were conducted (Good, 2005). In each simulation the residuals are repeatedly randomised over the counties and Moran's I is recalculated. This yields a distribution of simulated Moran's I values, which we compare to the observed value to obtain a p-value estimate.

metropolitan counties are statistically significant and robust to outliers. The number of online labour projects per county is positively associated with the 'Rural county' indicator variable (fourth row), controlled for several socio-economic factors. This finding holds across all model specifications (models 1 – 4a) and in all cross-validated samples (see the wide green bars). The zero-inflated negative binomial regression provides the best model fit both in term of in-sample goodness-of-fit (Tab 3A), and out-of-sample prediction accuracy (Fig. 3B, Fig. 3C). The high cross-validated out-of-sample correlation between the predicted number of projects and the test data of $\rho = 0.9$ underlines the good fit of model 4, which estimates the zero counts explicitly.

Figure 3 near here.

The model moreover identifies a positive association between the number of online projects and the number of firms per capita, the population size and the county education score. In other words, counties with a larger, better educated population and more firms tend to provide more online labour.

To give intuition for the magnitude of the rural county coefficient, we provide a numerical illustration from the non-linear model 4. Assuming all control variables of two counties — one rural and one metropolitan — had equal median values, the metropolitan county would be estimated to supply 13.1 projects and the rural county would be estimated to supply 21.7 projects. Thus, *ceteris paribus*, rural counties are estimated to provide approximately 66 % more online labour projects than metropolitan counties. This result supports the hypothesis that online labour markets are more intensively used in rural areas.

Model 5 also shows a positive association between the relative online skill score and the rural county indicator, although the relationship is less pronounced.[8] Counties with lower income, longer commuting times, and less firms tend to provide higher skilled online labour, which is in line with our hypothesis: specialists in rural areas, where local economic opportunities are rare, use online labour platforms more intensively to market their skills.

Despite this, only 45 % of all counties and 21 % of the rural counties in the contiguous United States participated in the online labour market at the time the data was collected (Fig. 4A and Tab. 4B). Participation tends to be geographically clustered: most of the metropolitan areas (dark green) in the densely populated coastal regions supply online labour, while large parts of the rural Midwestern United States do not.[9] Many of the active rural counties (light green) appear to be adjacent to metropolitan areas. However, the 'Adjacent to Metropolitan Statistical Area (MSA)' indicator variable (Tab. 3A) is not statistical significant in most of the regression models, and the Monte Carlo simulated Moran's I p-values do not provide evidence that the statistical results are driven by spatial autocorrelation.

Figure 4 near here.

Figure 4C suggests some potential factors behind these findings. Overall, it is the least pop-

[8]The dependent variable is defined only for participating counties, and thus the sample size in model 5 is restricted to 1,375 counties.

[9]The small white dots in the map represent the zip-code level centroids of online freelancers: most of them are clustered in the country's largest cities (black circles).

ulated, least urbanised counties that are less likely to supply online labour. This corresponds to the significant negative coefficient of population size in the zero-count model 4b (Tab. 3A). The non-participating counties tend also to have a slightly less educated population (Tab. 4B). Together with the non-significant 'Rural County' coefficient in model 4b, these observations indicate that it is not rural counties *per se* that are less likely to adopt online labour platforms, but rather the least urbanised areas with lowest education levels.

6. Discussion

ICTs have long been predicted to make cities as hubs of economic organisation obsolete and spread economic opportunities to rural areas (Cairncross, 1997; Graham, 1998). However, the actual trend in the 21st century has been the opposite. In the United States, ICT and media industry hubs such as San Francisco, Seattle, and New York continue to attract growing numbers of job-seekers, while deprivation in rural America has deepened (Clark et al., 2018; Glasmeier, 2018). We argued that one explanation for this 'urbanisation paradox' is that enhanced information flows alone are not enough to reorganise the geography of economic activity. In contrast to the 'death of distance' discourse (Cairncross, 1997) that predicted diminishing urban advantages due to ICT-enabled information flows, economic sociology and economic history have underlined the importance of 'systems of control' to ensure cooperation and to spark economic activity (Granovetter, 2005; Ogilvie, 2011). Thus, even though telecommuting and virtual teamwork have been common for long, actual job-seeking and hiring continued to favour proximate interactions, where local institutions and informal social controls can secure cooperation and establish trust (Granovetter, 1985).

In the empirical part of this article, we observed that in a small, but rapidly growing sliver of the ICT economy, the urban-rural divide appears to have been bucked: workers in rural American counties make disproportionately more use of the online labour market for project-based remote knowledge work. We argue that this is because online labour platforms have started to provide formal and informal cooperation enforcement mechanisms that extend over distance. Although ICT-mediated reputation systems and remote monitoring bring their own problems (Agrawal et al., 2016; Lehdonvirta et al., 2018; Wood et al., 2018b), they enable work to be contracted and delivered across distance. Accordingly, the rural Americans in our sample used the platform to obtain work online.

We found that rural counties supplied, on average, higher skilled online work than urban areas. This finding holds in relation to the general county education level, in absolute terms, and on top of common socio-economic control variables. According to our interpretation, this happens because incentives for skilled rural specialists are high to use the platform to access specialised demand beyond their local labour market. This finding has potentially substantial implications for regional development, because the presence and retention of highly skilled workers in a rural community is likely to positively affect the wider local economy (Roberts and Townsend, 2016). Despite these advantages, only a minority of rural counties participated in the online labour market at the time of data collection. The least populated and least educated — predominantly agricultural — regions of the country were least likely to participate.

This is concerning, because these regions tend to be most affected by rising spatial inequalities (Glasmeier, 2018). Not every county may be home to specialised workers with marketable skills. Such skills do not develop in vacuum: We found that most projects traded online referred to occupations closely associated with ICTs and other knowledge-intensive industries. Places that are home to such industries and related educational institutions are probably more likely to give rise to skilled online labour workforces. Thus, even with online labour markets there is no complete liberation from the 'tyranny of distance' (Virilio, 1993).

6.1. Limitations and future research

This study is the first to investigate urban-rural divides in online labour markets with highly granular geographic and occupation-specific data. The interpretation of the findings is constrained by the available online labour market data. The dataset is sparse and restricted to a six months time window. Thus, we are limited to report correlations, not causal relationships. To minimise uncertainty with respect to unobserved heterogeneity, we have restricted the study's scope to the relatively homogeneous United States, included important local socioeconomic control variables, carefully derived the statistical model specification and validated its robustness to outliers.

However, some heterogeneity, which we can not control for without time series data, remains in the county-level data, and even more on the individual level. Due to limited data availability, we could not explicitly address effects of local differences in Internet connectivity on the results, although it tends to be correlated with income and other variables included in the model. Other factors with potential effects on the geographic online labour disparities that we could not control for are regulatory differences that make independent contracting more or less desirable in different locations. Some disparities could also reflect differences in awareness of online labour platforms at the time of the study, which remain a relatively new innovation still in the process of rapid growth (Kässi and Lehdonvirta, 2018b). Such market dynamics might affect the evolving geographies in the future. All inferences reported here are made with these limitations in mind.

To test the generalisability of the findings, future work should extend the research on urban-rural divides in online labour market participation to other platforms and to more countries. In particular, longer transactions time-series data would make it possible to investigate spatial diffusion dynamics and the influence of local factors on the adoption likelihood in more detail.

Another important follow-up question that we could not address is whether rural online workers were better-educated locals or former city-professionals who escaped urban congestion and rising living costs. In the former case, our observations could be described as 'virtual migration' that helps retain human capital in rural areas. In the latter case, the situation could instead be described as 'virtual urbanisation' where work and human capital flow from cities to the countryside, with potentially substantial implications for future urban-rural dynamics.

Regardless, the study helps to reveal the potential and limitations of online labour as means of regional, in particular rural, development. Such an investigation is especially timely, as development agencies and other organisations have initiated programs that aim to use online labour platforms to promote economic development in the world's more remote regions (Suominen, 2017). Against this background, it is important to understand the prospects of this new trend for rural areas.

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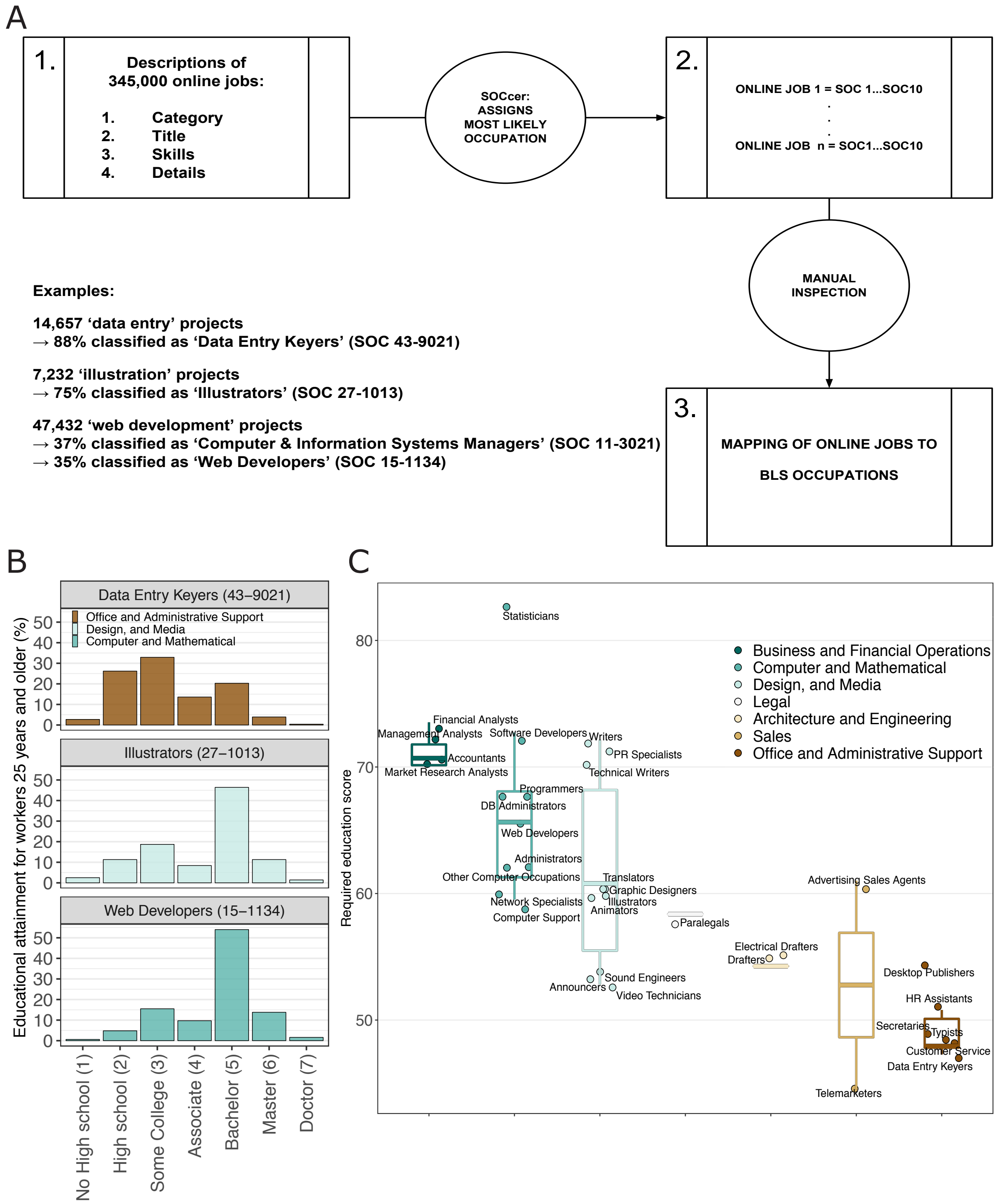


Fig. 1.. (**A**) Mapping of online jobs to SOC: 1. the category, title, required skills and details of all online projecs are fed into the SOCcer classifier. 2. The tool yields ten suggested SOC codes per project. 3. The results are manually inspected and matched with the most likely and reasonable SOC occupation. (**B**) Educational attainment distributions of different occupations, used to calculate a required skill score per occupation (**C**) Derived required skill scores of all occupations in the dataset, which vary substantially between the categories.

A

	Metropolitan Central	Metropolitan Outlying	Micropolitan Central	Micropolitan Outlying	Rural
Online Labour (county medians)					
Demand	50	6	4	0	0
Demand per 10,000 inhabitants	2.53	1.17	0.72	0.00	0.00
Supply	19	4	4	2	3
Supply per 10,000 inhabitants	0.89	0.93	0.88	2.26	1.54
Education / skills (county means)					
Online skill level	64.1	65.2	64.5	63.5	65.4
County education level	69.6	65.4	65.5	62.6	62.9
Relative Online skill level	0.92	0.97	0.97	1.00	1.01
Population					
Number of counties	648	180	301	19	286
Median population size (tsd.)	171	50	47	13	20
Average share of urban population (%)	80	43	54	17	22
Economic factors					
Average unemployment rate (%)	9.3	9.3	9.8	9.2	9.4
Median commuting time (min.)	24	28	21	25	24
Median household income (tsd. $)	51.5	50.8	42.9	42.9	40.5
Median number of firms per 10,000 inhabitants	0.82	0.77	0.75	0.81	0.84

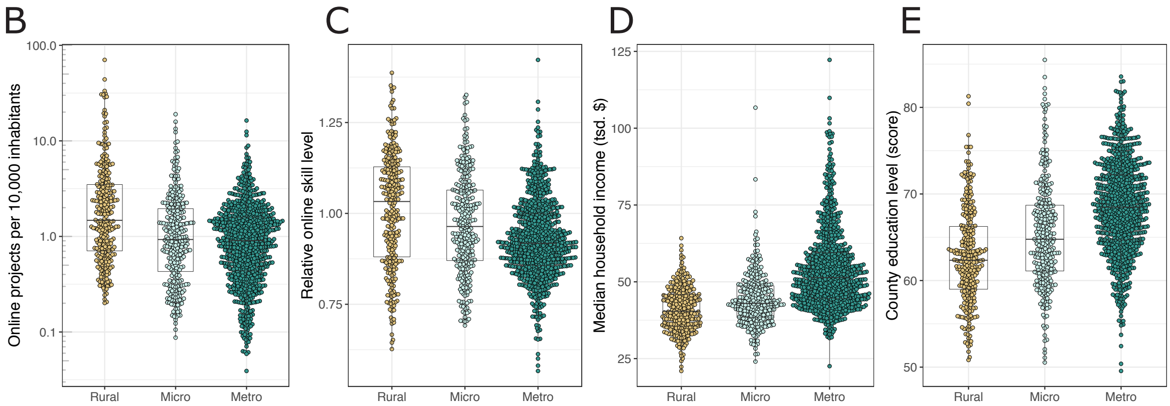


Fig. 2.. (**A**) Summary statistics of online labour demand and supply, skill level, population and economic factors in metropolitan, micropolitan, and rural counties. (**B-E**) Distributions of the number of projects per capita, relative online skill score, median household income, and county education score in metropolitan, micropolitan, and rural counties. Rural counties tend to supply more online labour that is of higher skill level than urban areas.

A

	Dependent variable: number of online labour projects					*Rel. skill score*
	OLS	*Poisson GLM*	*Negative binomial*	*Zero-inflated model count*	*Zero-inflated model zeroes*	*OLS*
	(1) CV signf.*	(2) CV signf.	(3) CV signf.	(4a) CV signf.	(4b) CV signf.	(5) CV signf.
No. of firms (per capita, log-10)	33.75*** (6.10)	0.94*** (0.07)	1.09*** (0.33)	1.22*** (0.32)	-0.12 (0.59)	-0.22*** (0.03)
Population size (log-10)	38.25*** (1.54)	2.46*** (0.01)	2.59*** (0.08)	1.91*** (0.07)	-3.31*** (0.21)	-0.01 (0.01)
County education (score)	0.44*** (0.15)	0.05*** (0.002)	0.05*** (0.01)	0.03*** (0.01)	-0.08*** (0.01)	
Rural county (indicator)	11.32*** (2.13)	0.27*** (0.03)	0.34*** (0.11)	0.51*** (0.11)	-0.06 (0.18)	0.03* (0.01)
Micropol. county (indicator)	-4.02** (2.04)	0.02 (0.03)	0.18* (0.10)	0.01 (0.09)	0.15 (0.18)	0.02* (0.01)
Unemployment (%)	-0.28 (0.24)	0.01*** (0.003)	0.01 (0.01)	-0.01 (0.01)	-0.01 (0.02)	-0.01*** (0.00)
Med. commuting time (minutes)	0.30** (0.15)	-0.01*** (0.002)	0.02** (0.01)	0.01 (0.01)	-0.01 (0.01)	0.06*** (0.00)
Med. HH income (USD, log-10)	-14.22 (10.63)	-1.00*** (0.10)	-0.50 (0.54)	-0.84 (0.52)	0.47 (1.03)	-0.51*** (0.05)
Adjacent to MSA (indicator)	-7.67*** (2.82)	0.22*** (0.07)	0.02 (0.16)	-0.11 (0.20)	-0.03 (0.26)	0.00 (0.01)
Constant	-86.89* (46.24)	-7.90*** (0.42)	-11.10*** (2.33)	-4.00* (2.27)	17.38*** (4.54)	2.98*** (0.23)
Observations	3,052	3,052	3,052	3,052	3,052	1,375
θ			0.41*** (0.02)	1.02*** (0.05)		
Log Likelihood	-15,318.16	-13,166.03	-6,293.16	-5,993.58		$R^2 = 0.24$
Akaike Inf. Crit.	30,656.32	26,352.05	12,606.33	12,029.17		
Out-of-sample goodness-of-fit measures (10-fold cross-validated)						
Mean Abs. Err. (SDs)	14.75 (1.47)	9.79 (1.98)	9.80 (1.98)	6.08 (1.17)		0.09 (0.01)
Pearson's ρ (SDs)	0.58 (0.07)	0.55 (0.07)	0.56 (0.07)	0.90 (0.04)		0.45 (0.07)
Spatial autocorrelation						
Moran's I (p-value) (1,000 Monte Carlo simulations)	0.00 (0.67)	0.01 (0.16)	0.02 (0.08)	0.01 (0.11)		0.03 (0.07)

*The bars show how often a parameter estimate was statistically significant in the ten re-sampled cross-validated (CV) datasets — > 0; < 0

*p<0.05; **p<0.01; ***p<0.001

B C

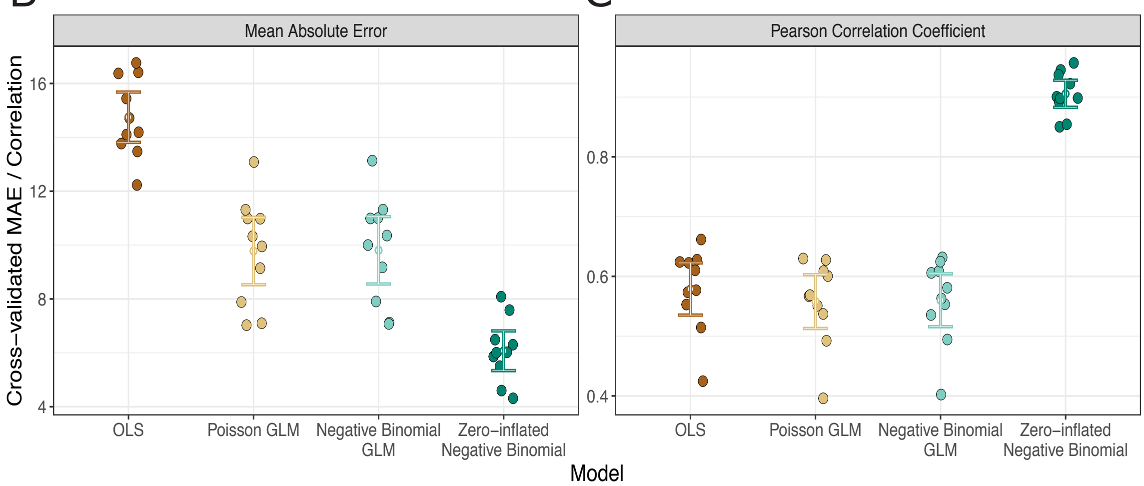
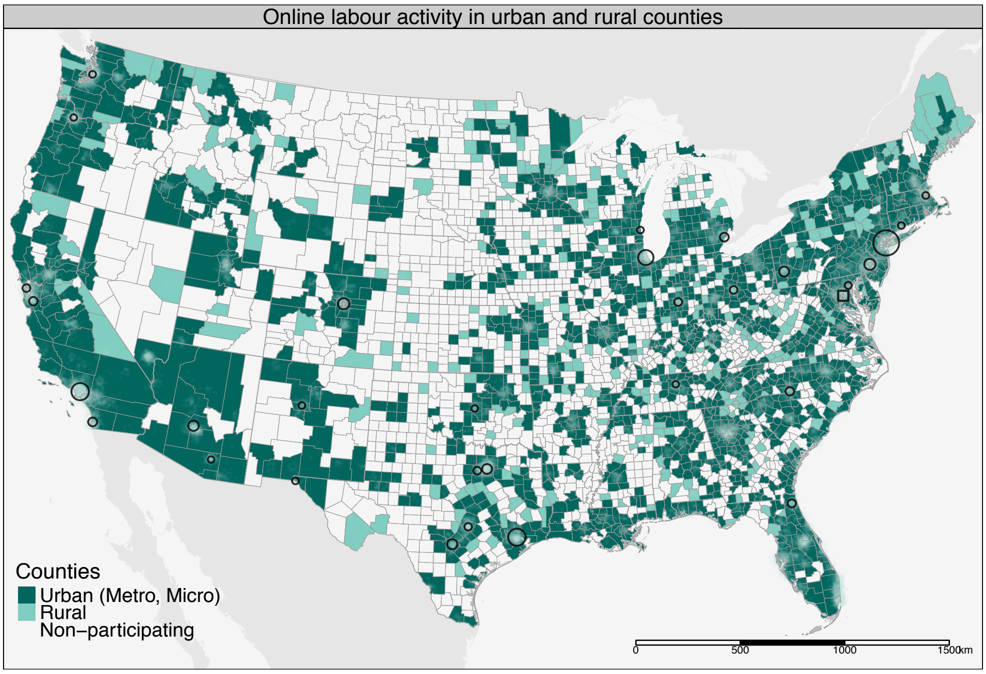


Fig. 3.. (**A**) Regression models associating the number of online labour projects and the relative online skill level to regional indicators and socio-economic control variables: rural areas provide significantly more and higher skilled online labour than urban centres. (**B-C**) Out-of-sample Mean Absolute Error and Pearson Correlation Coefficient: the zero-inflated negative binomial model performs best (dots represent cross-validated prediction results; error bars show mean $\pm\ 2 \cdot SD$).

A



B

Rural online labour market activity	yes	no
Online Labour (county medians)		
Demand	0	0
Demand per 10,000 inhabitants	0	0
Supply	3	—
Supply per 10,000 inhabitants	1.54	—
Education / skills (county means)		
Online skill level	65.4	—
County education level	62.9	62.6
Relative Online skill level	1.01	—
Population		
Number of counties	286	1026
Median population size (tsd.)	20	10
Average share of urban population (%)	22	21
Economic factors		
Average unemployment rate (%)	9.4	8.3
Median commuting time (min.)	24	21
Median income (tsd. $)	40.5	40.6
Median no. of firms per 10,000 inhabitants	0.84	0.85
Shared boundaries with urban areas (% of rural counties)		
Adjacent to Metropolitan area	81	75
Adjacenct to Metro- / Micropolitan area	90	86

C

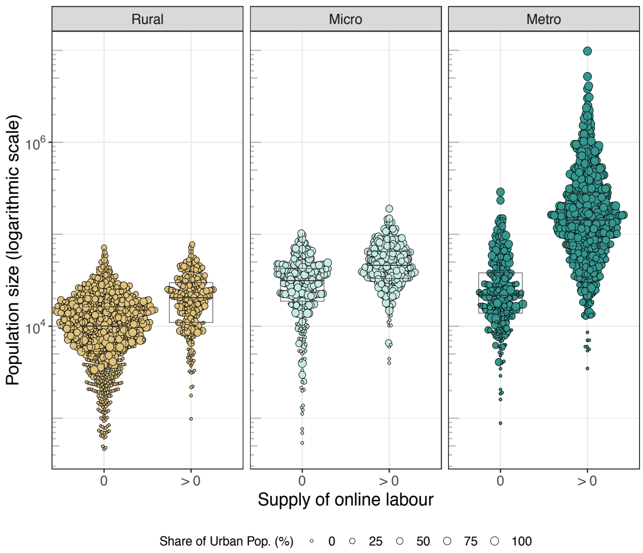


Fig. 4.. (**A**) U.S. continental map highlighting urban areas (dark green) and rural counties (light green) supplying online labour, and non-participating counties (white). (**B**) Summary statistics of participating and non-participating rural counties. (**C**) Distribution of population size and share of urban population in participating and non-participating metropolitan, micropolitan, and rural counties: independently of the county type, it is the less populated and less urbanised counties that do not participate.