Impacts of Online Labour Markets on Rural Employment

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Abstract

Urbanization is one of the megatrends of the 21st century. People flock to urban centres thanks to the availability of jobs and other opportunities. This process can lead to deprivation in rural areas. Now, online labour platforms have fuelled hopes to alleviate the urban-rural divide, as the technology has started to re-imagine the entire work process by enabling work to be delivered across distance. However, urban-rural differences in the use of online labour platforms remain poorly understood. In this study, we examine sub-national differences in worker's use of online labour platforms in the United States to evaluate whether such platforms have helped people in rural regions to get work that they could not have found in their local labour markets. In developing novel county-level measures of online labour supply, we find that workers in rural American counties make disproportionately more use of the opportunities provided by the online labour market. This applies especially to skilled workers, whose presence and retention in rural areas is likely to be important for the wider local economy. The study helps to better understand the potential and scope of online labour platforms as means of regional development.

JEL classification: J 24, J 61, L 17, R 12

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1. Introduction

Urbanization is one of the megatrends of the 21st century (Clark et al., 2018; Glaeser et al., 2001). People flock to urban centres thanks to the availability of jobs and other opportunities. Short distances in cities allow ideas and knowledge to move easily from one person and workplace to another (Florida and Mellander, 2018; Florida et al., 2011; Glaeser and Kahn, 2004). But this geographic concentration brings problems, too: congestion in urban centres, and deprivation in rural areas. The Internet has fuelled hopes that technology could eventually alleviate the urban-rural divide, by allowing information to flow freely across long distances (Kok and Weel, 2014; Forman et al., 2018; Gaspar and Glaeser, 1998; Friedman, 2005; Cairncross, 1997; Graham, 2008).

Yet actual outcomes have been mixed: research suggests that larger cities have so far benefited disproportionally from reduced communication and search costs associated with the Internet (Forman et al., 2018; Forman, 2014). Telecommuting and virtual teamwork have become reality, but getting hired in the first place remains much easier in cities than rural areas. Online job boards replaced newspaper advertisements, but the hiring processes retained other location-specific parts, such as face-to-face interviews.

However, online labour platforms have now started to re-imagine the entire hiring and work process. By enabling workers and employers to find each other, conclude contracts, and deliver work without being physically in the same location, online labour markets may finally be delivering on the Internet's promise to bring new economic opportunities to rural areas (Manyika et al., 2015; Kuek et al., 2015).

[1] `https://reshapingwork.net/`

Urban-rural differences in the use of online labour platforms remain poorly understood in the research literature. Research on the geography of online labour markets has mostly focused on the country level (Horton et al., 2017; Kässi and Lehdonvirta, 2018), and on geographical frictions that affect the international service trade via these platforms (Ghani et al., 2014; Hong and Pavlou, 2014; Beerepoot and Lambregts, 2015; Galperin and Greppi, 2017). To our knowledge, only one study (Borchert et al., 2018) considers the effect of local economic factors on the economic geography of online labour markets.

In this study, we therefore examine sub-national differences in worker's use of online labour platforms to empirically evaluate whether such platforms have helped people in rural regions to get work that they could not have found in their local labour markets. To achieve this, we match geocoded transactions data from a leading online labour platform with data from the U.S. Census Bureau and the Bureau of Labour Statistics. This matching allows us to analyse differences in usage patterns between urban and rural areas with high geographic granularity.

2. Theory and Hypotheses

Rural areas generally offer fewer employment opportunities than urban areas, leading job-seekers to move to urban areas (Greenwood, 1997; Lucas, 2004; Glasmeier, 2018). Online labour platforms have been posited to offer and alternative to such employment-based migration, constituting a form of 'virtual migration' (Ipeirotis and Horton, 2011). Our first hypothesis is thus:

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

However, it is also important to consider the composition of the labour being supplied. It is well understood that cities can support more specialised jobs than rural areas (Sveikauskas, 1975; Quigley, 1998; Bettencourt et al., 2014). Productivity gains from learning drive specialization, and the larger a city's size, the more fine-grained its potential division of labour is. Consequently, cities feature far greater occupational diversity than rural areas, with skilled specialists commanding higher wages than undifferentiated generalists. In contrast, in rural areas employers are sparse, and narrow specialists will find it difficult to secure enough work to maintain their specialisms. Instead, they will likely have to accept more generalist and less well remunerated tasks. If online labour platforms alleviate geographic constraints on job search, then this should disproportionately benefit people with specialised skills in rural areas, as the platforms connect these workers to specialised demand beyond their local areas. Urban specialists already enjoy ample local demand for their skills, so platforms are comparatively less useful to them. Since urban areas have adapted to provide specialised education to more people than rural areas do, we also need to account for the general education level in an area when examining this issue. Our second hypothesis is therefore:

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

3. Research Design

Our overall approach to examining the hypotheses is as follows. Focusing on the United States, we construct novel county-level measures of online labour supply, skill level of the online labour supply, and general education level in the county. We then perform cross tabulations, graphical analyses, and regression analyses of these measures together with other county-level data, and in particular whether the county is classified as metropolitan, micropolitan, or rural. This allows us to compare urban and rural areas in the United States in terms of their online labour supply in the presence of appropriate controls.

3.1. Data Sources

Our measures of online labour supply are derived from a data set consisting of all transactions on a leading online labour platform carried out between 1 March 2013 and 31 August 2013. The data set comprises 362,989 projects and includes each project's job category (one of 34 possible categories) and the worker's location on a zip code level

The platform serves as an intermediary, matching freelance workers with clients and facilitating the entire contracting relationship from search and negotiation to supervision, delivery, billing, post-project evaluation, and dispute resolution. The platform uses a double auction model, where both clients and providers are able to make offers and therefore influence pay rates; the platform charges a fee of approximately 10 %.[2]

In this study we focus on projects where the contractors are located in the United States. This is because the study 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. To ensure that our findings speak to urban-rural differences and are not the result of statistical artefacts, in this study we therefore limit ourselves to the United States. Filtering the dataset leaves us with 34,198 projects conducted by U. S. freelancers.

To aggregate the platform transaction data to the county level used in official U.S. statistics, we geocode the dataset using the *Google Geocoding API* and aggregate them to polygonal shapefiles available from the U. S. Census Bureau.[3]

All county-level economic and demographic data come from the U. S. Census Bureau American Community Survey (US-Census, 2016). We collected the population estimate, the share of urban population, educational attainment of the adult population (25 years and over), mean travel time to work (minutes), median household income (U. S. dollars), and the unemployment rate.

To operationalise the urban-rural distinction, we use the classification system of the U.S. Office of Management and Budget, which classifies each county as belonging into either a rural, micropolitan, or metropolitan area. An important characteristic of this classification system is that it turns on population concentration rather than on population numbers alone, and is thus in line with the economic theorising on geographic concentration. A metropolitan area, according to this system, is an area that contains a core urban agglomeration of 50,000 or more population. A micropolitan area contains an urban core of at least 10,000, but less than 50,000, population. All other areas are rural areas. Note that a county can belong to a metropolitan area without itself having 50,000 inhabitants, and that a county can have a population in excess of 10,000 and still be rural, if the population is not concentrated to any urban core. Raw population numbers are of course also significant for economic outcomes, and we include them in our models alongside this classification system.

3.2. Determining the skill level of online labour supply

To address H2, we need a way to assess the required skill level of the online labour supplied from each county. To do so, we map the online labour platform's project categorisation system to the Standard Occupation Classification (SOC) system, used by the U. S. Bureau of Labour Statistics, and use educational attainment data associated with the latter to calculate an estimated educational attainment or skill score for each online labour job category. Some of the disadvantages of this method are that the mapping is far from perfect, assessing skill demands on the category/occupation level misses variation on the individual project level, and educational qualifications do not strictly equate to skills or specialisation. Important advantages of this method are that it yields a common measure that can be applied across different types

[2]Details of the dataset are described in (Lehdonvirta et al., 2018).
[3]`https://www.census.gov/geo/maps-data/data/cbf/cbf_description.html`

of online labour, and that it provides comparability with the overall education level of a county, which is measured in the same educational attainment terms.

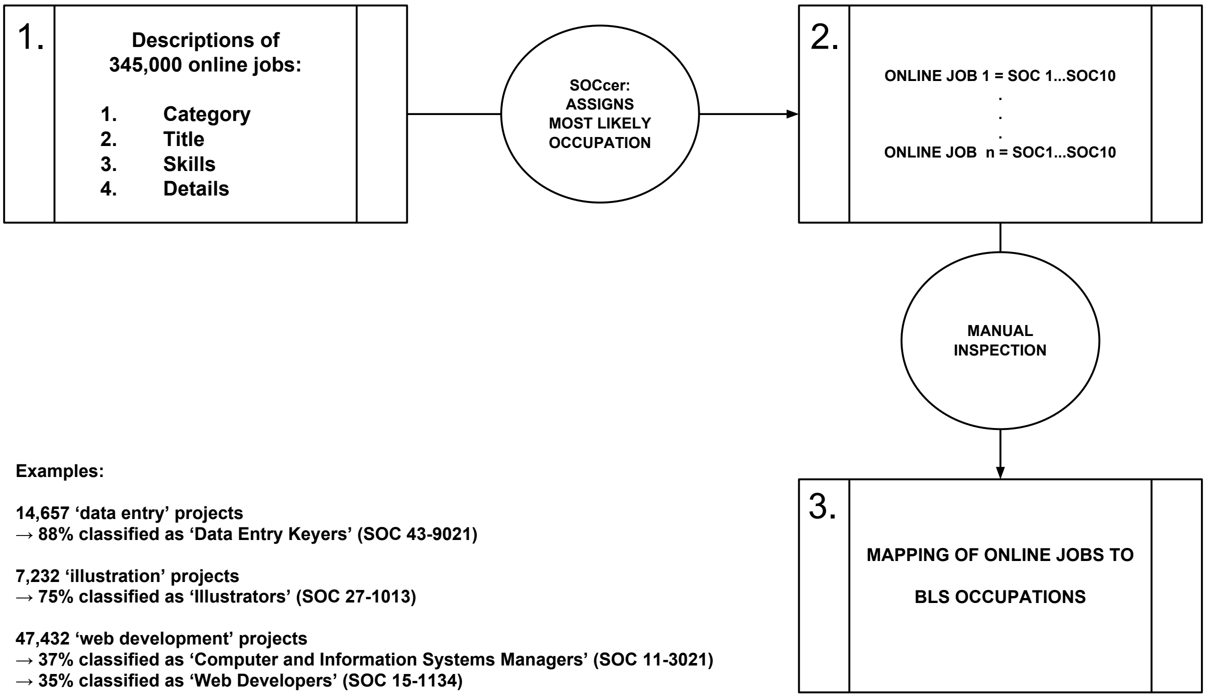

Fig. 1. Illustration of the occupation matching methodology: (1) Of all 345,000 projects collected from the platform, online job category, project title, required skills and project details are extracted. (2) For each project, this information is fed into the SOCcer ensemble classifier, which yields ten suggested SOC occupation codes per project. (3) The results are manually inspected for each online job category and matched with the most likely and reasonable SOC occupation. For example, 88 % of all 'data entry' projects are classified as 'Data Entry Keyers', an obviously good match. 37 % of the 'web development' projects are classified as 'Computer and Information Systems Managers'. This online job category was manually assigned to the occupation 'Web Developers', to which only 35 % of the projects were classified, but which is a better fit.

For the mapping procedure, we employ the 'SOCcer' tool (Russ et al., 2016), an online application developed by the National Institutes of Health that matches free-text job information to SOC 2010 occupation codes using and ensemble classifier. The methodology is illustrated in figure 1. As the 2013 transactions dataset does not include all relevant details of each project, we collected an additional dataset from the online labour platform using the platform's API in January 2016, consisting a random sample of the transaction histories of 46,791 freelancers.[4] This dataset is only used here for the purposes of mapping online project categories with SOC classifications.

The dataset used for the mapping contains 345,000 project and includes each project's category (under the platform's categorisation system), title, skill requirements (as indicated by the employer), and a free-text description (element 1. in figure 1). Each project is fed into the SOCcer classifier. The tool provides the 10 highest scoring SOC codes for each free-text job description (element 2.). As there are 840 occupations in the SOC system, and as the descriptions of each online project differ, similar online projects could be assigned to different occupations. To obtain a reasonable matching, the results of all online jobs of a category are aggregated and manually inspected (element 3.). If the highest scoring occupation, as suggested by the SOCcer tool, does not provide a meaningful match, the results-list was searched for the next highest scoring meaningful occupation. Additionally, the SOC definitions of the matched occupations were consulted and compared to projects of the each category to ensure reliability.[5]

The examples shown in figure 1 illustrate the matching-process: 88 % of the 14,657 'data entry' online

[4]Details of this dataset are described in (Kässi, 2018).
[5]`https://www.bls.gov/soc/soc_2010_definitions.pdf`

projects were assigned to the occupation 'Data Entry Keyers' (SOC-code 43-9021) by the ensemble classifier. This is an obviousls good fit: the vast majority of projects of this category are all classified into the same occupation, and the exemplary projects that were manually inspected match the occupation definitions provided by the Bureau of Labour Statistics. Hence, all 'data entry' jobs are matched to 'Data Entry Keyers'. Similarly, 75 % of the 7,232 'illustration' projects were assigned to the SOC-code 27-1013, referring to Illustrators.

In contrast, only 37 % of the 47,432 'web development' projects were assigned to the highest scoring occupation 'Computer and System Managers'. 35 % were classified as 'Web Developers'. This undetermined result corresponds to the variation in the descriptions of the online projects and to the similarity of the suggested occupations. The SOC-definition of 'Web Developers' describes a job in the category '15-0000 Computer and Mathematical Occupations'. This is a better fit than the definition of 'Computer and Systems Managers', which is part of '11-0000 Management Occupations'. Accordingly, the 'web development' online projects were assigned to the occupation 'Web Developers' (SOC-code 15-1134). In summary, the online jobs are assigned into 34 different occupations in seven occupational groups.

This matching procedure allows us to calculate the required educational or skill level of online jobs as a numerical value that can be compared across different occupations. To do so, we use the occupation specific educational attainment statistics provided by the Bureau of Labour Statistics (BLS, 2016). Figure 2 shows the educational attainment distributions of the three previously mentioned occupations. To calculate a numerical score from these distributions, which represent the required educational level, we multiply the proportion of workers in each of the seven educational levels with Likert scale values from 1 to 7, sum them and take the average. The figure provides an example: 3 % of the Data Entry Keyers have no high school diploma (level 1), 26 % have a high school diploma (level 2), 33 % have some college education (level 3), 14 % have an Associate's degree (level 4), 20 % have a Bachelor's degree (level 5), 4 % a Master's degree (level 6), and 1 % a Doctoral degree (level 7). Accordingly, the overall score of Data Entry Keyers is 48. Equivalently, the score of Illustrators is 60 and the score of Web Developers is 65.

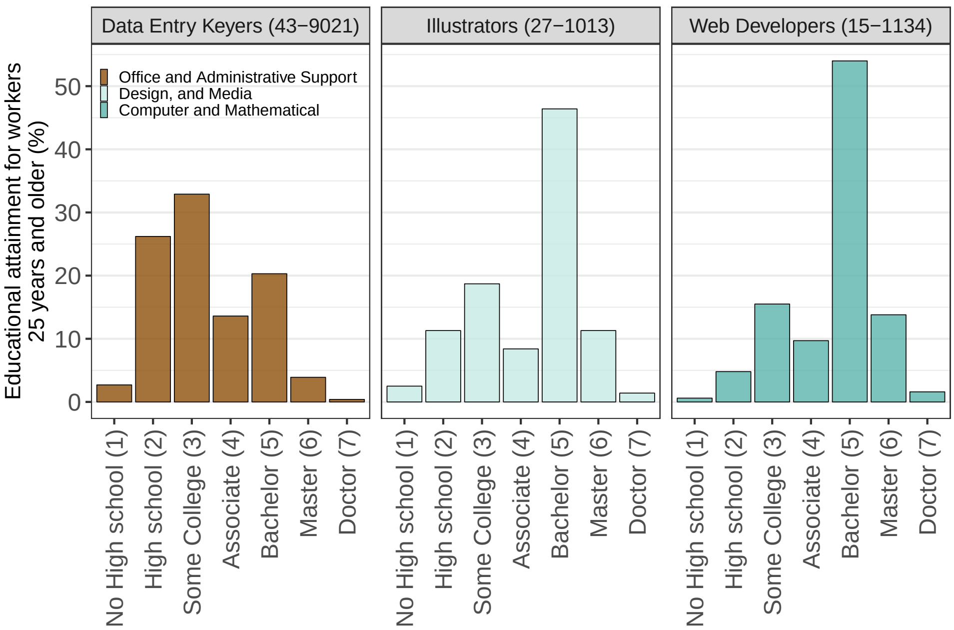

Fig. 2. Educational attainment distributions of three occupations from the U. S. Bureau of Labour Statistics. These distributions are the basis to calculate the required education Likert scale in multiplying the proportion of workers in each education level by the value displayed in parentheses and dividing by the number of groups. For example, for the example of Data Entry Keyers:

$$(3\,\% \cdot 1 + 26\,\% \cdot 2 + 33\,\% \cdot 3 + 14\,\% \cdot 4 + 20\,\% \cdot 5 + 4\,\% \cdot 6 + 1\,\% \cdot 7)/7 = 48$$

The reasoning behind this calculation is that the educational attainment distribution corresponds to the skill level that is required to perform a job. Calculating one numerical value per occupation to capture the educational requirement is obviously a simplification, and the resulting score is only a rough approximation as all the variation in task contents is ignored. However, it gives us one common scale to differentiate the online jobs by skill level. This is what we need to answer the research question.

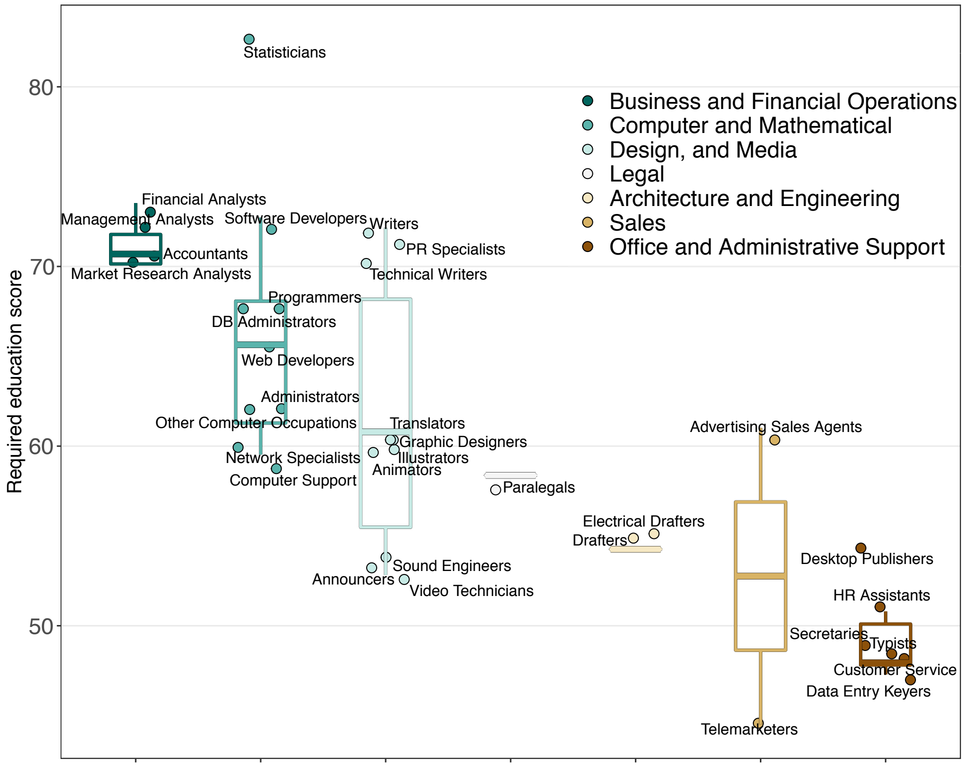

Fig. 3. Estimated required education levels of 34 occupations in the dataset. The educational requirements of the different jobs vary substantially between the categories: for example, the median score in the category 'Office and Administrative Support' is 48, it is 60 in the category 'Design, and Media', and 65 in the category 'Computer and Mathematical' occupations.

The score-calculation is done for all 34 occupations in the dataset. The resulting scores are displayed in figure 3. The scores vary substantially between and within the occupational groups. For example, the median score of the jobs in the category 'Office and Administrative Support' is 48, while it is 65 in the category 'Computer and Mathematical'.

In the last step to calculate an indicator that allows us to compare the online labour skill levels of rural and urban counties, we calculate the average required education score of the online jobs in each county and divide it by a score that captures the educational distribution of a county's population. This score is computed equivalently to the occupation specific score. We multiply the proportion of people in a given educational level with the corresponding Likert scale value, add them up and take the average. This yields an overall score that is on the same scale as the occupation specific score. Dividing both scores yields a ratio: values larger (smaller) than one imply that the online jobs done by freelancers in a county are of a higher (lower) educational level than the average educational level of the county. This relative measure allows us to compare the online job educational levels between counties, as differences due to the educational level of a county's population are accounted for.

4. Results

Within the U. S., substantial differences exist in the online labour market participation of rural and urban areas (figure 4). While metropolitan counties provide more online labour in absolute terms, rural

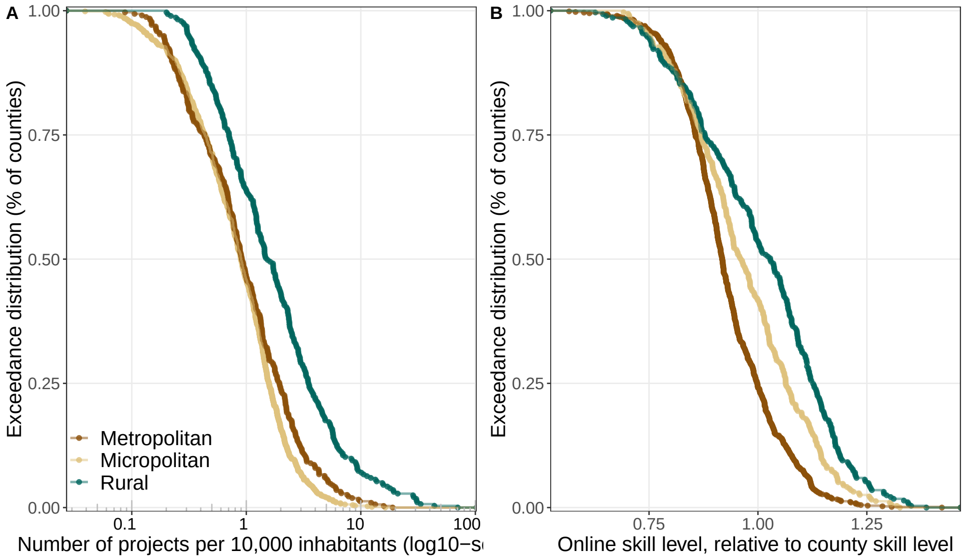

Fig. 4. Exceedance distributions of (A) the number of online projects per 10,000 inhabitants and (B) the relative online skill level in metropolitan, micropolitan and rural counties. In per-capita terms, rural counties provide more online labour projects than metropolitan or micropolitan areas: while 64 % of the rural counties provide more than 1 project per 10,000 inhabitants, only 46 % of the metropolitan areas do so. Additionally, rural areas provide higher-skill online labour than urban areas, in relation to the education level of the county-population: 53 % of rural areas and only 42 % of the metropolitan areas show a relative online skill level larger then one.

areas are more active in per capita terms (panel A). The results reported in Figure 4, Panel A indicate that 64 % of the rural counties in the dataset provide more than 1 project per 10,000 inhabitants, while only 46 % of the metropolitan counties do so. This finding is in line with H1: Rural areas supply more online labour proportional to population than urban areas do. Descriptive statistics reported in Table 1 lend support to the notion that this disparity stems from differences in local economic opportunities between urban and rural areas. They show that the median household income is substantially higher in metropolitan than in rural counties, while other economic factors do not differ notably between these county classes.

The findings moreover show that rural areas provide relatively more skilled online labour (panel B): 53 % of the participating rural counties provide online labour that has a higher required education score than the county population. In contrast, only 42 % of the micropolitan counties and 24 % of the metropolitan counties do so. These findings offer support to H2: Rural areas supply more skilled online labour proportional to their general education level than urban areas do. In fact, the average skill level of online labour supplied from rural areas is slightly higher even in absolute terms than that from metropolitan and micropolitan counties (Table 1). This is despite the average educational level in metropolitan counties being notably higher than in rural countries. These findings lend credibility to the notion that highly skilled individuals in rural areas especially benefit from online labour markets. Table 1 also confirms that the vast majority of online labour demand comes from urban centres, which is in line with our theoretical framework.

These differences in online labour market participation between rural and urban areas are statistically significant and robust to important control variables (table 2). Controlled for population size and economic factors, rural areas provide significantly more online labour than urban areas (model 1), as indicated by the negative coefficients of the metropolitan and micropolitan area indicators. Additionally, rural counties provide higher skilled online labour than metropolitan counties (model 2). The negative coefficient of median income moreover indicates that it is poorer counties that are more active.

One puzzle that the results turn up is that despite rural areas benefiting disproportionately from the online labour platform, only a minority (21 %) of American rural counties actually participate in

Tab. 1. Summary statistics of online labour demand and supply, skill level, population and economic factors per county in metropolitan, micropolitan and rural areas. Central metropolitan areas account for the majority of online labour demand and supply in absolute terms. Rural areas and outlying metropolitan counties show the highest average skill levels of the online workforce.

	Metropolitan		Micropolitan		Rural
	Central	Outlying	Central	Outlying	
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

it (table 3). This could be due to a number of factors. It could reflect disparities in the geographic distribution of skilled workers: not every county may be home to workers with marketable skills. It could also reflect regulatory differences that make self-employment more or less desirable in different locations. It could reflect differences in Internet access and other infrastructure. And it could simply reflect uneven geographic diffusion in awareness and adoption of online labour platforms, which at the time of the data collection were still a relatively new innovation, and still remain in rapid growth (Kässi and Lehdonvirta, 2018).

Although we are not able to address this puzzle comprehensively in this paper, some patterns in non-participation are evident. Considering the geography of the participating rural counties (figure 5) in relation to counties containing urban agglomerations reveals that most of the active rural counties are close to metropolitan areas. Large parts of the rural Midwestern and Southern United States are not participating in the online labour market. With a median population size of 20,000, the participating counties are considerably larger than the non-participating counties with a median population of 10,000 (table 3). They are also less remote in terms of adjacency to urban agglomerations: 81 % of the participating rural areas share at least one boundary with a metropolitan county, in contrast to 75 % of the non-participating counties.

5. Discussion

The Internet has long been promised to spread economic opportunities and alleviate geographic disparity between urban and rural areas, yet the actual trend in the 21st century has been largely the opposite. This study suggests that in a small sliver of the economy, the trend has now been bucked: workers in rural American counties make disproportionately more use of the opportunities provided by the online labour market. This applies especially to skilled workers, whose presence and retention in rural areas is likely to be important for the wider local economy as well. According to our interpretation,

Tab. 2. Regression models on (1) the number of online labour projects and (2) the relative online skill level. Controlled for the population size and economic factors, rural areas provide significantly more online labour than metropolitan or micropolitan regions. Relative to the county's education level, rural areas provide higher skilled online labour than urban centres.

Dependent variable	Number of online labour projects (1)	Relative online skill level (2)
Commuting time	0.004	0.01***
	(0.003)	(0.001)
Median income (log-10)	-0.37*	-0.51***
	(0.20)	(0.04)
Unemployment rate	-0.01	-0.01***
	(0.01)	(0.001)
Firms per capita (log-10)	0.46***	-0.22***
	(0.13)	(0.03)
Population (log-10)	0.84***	-0.004
	(0.03)	(0.008)
County education level	0.01***	
	(0.003)	
Metropolitan area indicator	-0.20***	-0.03***
	(0.04)	(0.01)
Micropolitan area indicator	-0.20***	-0.01
	(0.04)	(0.01)
Constant	-1.71**	3.01***
	(0.84)	(0.22)
Observations (counties)	1,385	1,385
R^2	0.53	0.23
Adjusted R^2	0.52	0.23
Residual Std. Error	0.43 (df = 1376)	0.12 (df = 1377)
F Statistic	192.13*** (df = 8; 1376)	60.06*** (df = 7; 1377)

Note: *p<0.1; **p<0.05; ***p<0.01; Standard-errors in parentheses.

this happens because the online labour market allows skilled specialists to access demand for their skills beyond their local labour market, thus allowing them to maintain their specialism without migrating to an urban area with a larger and more diverse local labour market.

Although in this study we focused on the online labour platform as the enabling technology, the findings are likely attributable to a constellation of complementary technologies. Besides the platform itself that provides matching, contracting, and other crucial functions, a thriving online labour market is also likely to require technologies such as electronic payments, cloud-based collaboration tools, and video conferencing, used for job interviews and project communications. All of these rely on high-quality Internet connectivity, which could be one reason why we find that the online labour market has not reached the most remote regions of the country, which tend to be the most affected by rising inequalities and losses from urbanisation (Glasmeier, 2018). This is one important avenue for follow-up research.

In developing a method to map online labour projects to the Standard Occupation Classification system, this study is the first to investigate urban-rural divides in online labour markets with granular geographic and occupation-specific data. The study's scope is constrained by the limitations of the available online labour market data. The dataset is sparse and restricted to a six months time window. A longer transactions time-series would allow us to investigate the urban-rural dynamcics in more detail.

Nonetheless, the study helps to better understand the potential and scope of online labour platforms as means of regional development. This is especially timely, as development agencies and other organisations have initiated programs that aim to use online labour as a means to promote economic development in the world's more remote regions (Suominen, 2017).

Tab. 3. Summary statistics of online labour providing rural areas in contrast to other rural counties. Almost 80 % of the U. S. rural counties do not participate in the online labour market. The non-participating counties are less populated and farther away from urban centres than the participating counties.

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 number of firms per 10,000 inhabitants	0.84	0.85
Shared boundaries with uraban areas (% of rural counties)		
Adjacent to Metropolitan area	81	75
Adjacenct to Metro- / Micropolitan area	90	86

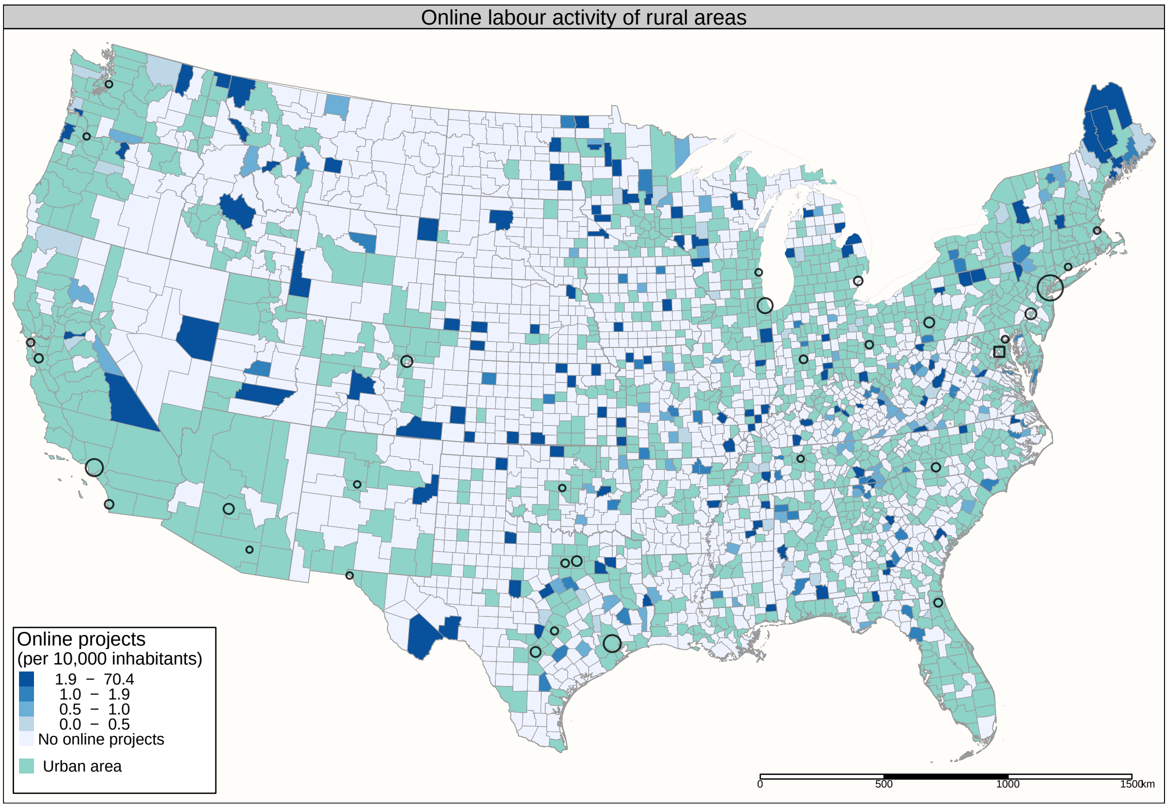

Fig. 5. U. S. continental map highlighting urban areas (green), online labour providing rural counties (blues) and other rural counties (grey). Most of the rural counties that participate in the online labour market are adjacent to metropolitan or micropolitan areas.

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