The global polarisation of remote work

Fabian Braesemann^{a,b,c}, Fabian Stephany^{a,b,c}, Ole Teutloff^{c,d},
Otto Kässi^{a,e}, Mark Graham^a, Vili Lehdonvirta^a

^aOxford Internet Institute, University of Oxford, Oxford, United Kingdom

^bHumboldt Institute for Internet and Society, Berlin, Germany

^cDWG Datenwissenschaftliche Gesellschaft Berlin, Berlin, Germany

^dCopenhagen Center for Social Data Science, University of Copenhagen, Copenhagen, Denmark

^eEtla Economic Research Helsinki, Finland

Correspondence: fabian.braesemann@oii.ox.ac.uk

November 1, 2022

This is an Accepted Manuscript of an article published in the journal *PLOS ONE*.

The original source of publication is:

Braesemann, F., Stephany, F., Teutloff, O., Kässi, O., Graham, M., Lehdonvirta, V. (2022).

The global polarisation of remote work. *PloS one*, 17(10), e0274630.

<https://doi.org/10.1371/journal.pone.0274630>.

Available online:

<https://journals.plos.org/plosone/article?id=10.1371/journal.pone.0274630>

Supporting Information available here:

<https://doi.org/10.1371/journal.pone.0274630.s001>

Abstract

The Covid-19 pandemic has led to the rise of digitally enabled remote work with consequences for the global division of labour. Remote work could connect labour markets, but it might also increase spatial polarisation. However, our understanding of the geographies of remote work is limited. Specifically, in how far could remote work connect employers and workers in different countries? Does it bring jobs to rural areas because of lower living costs, or does it concentrate in large cities? And how do skill requirements affect competition for employment and wages? We use data from a fully remote labour market—an online labour platform—to show that remote platform work is polarised along three dimensions. First, countries are globally divided: North American, European, and South Asian remote platform workers attract most jobs, while many Global South countries participate only marginally. Secondly, remote jobs are pulled to large cities; rural areas fall behind. Thirdly, remote work is polarised along the skill axis: workers with in-demand skills attract profitable jobs, while others face intense competition and obtain low wages. The findings suggest that agglomerative forces linked to the unequal spatial distribution of skills, human capital, and opportunities shape the global geography of remote work. These forces pull remote work to places with institutions that foster specialisation and complex economic activities, i.e. metropolitan areas focused on information and communication technologies. Locations without access to these enabling institutions—in many cases, rural areas—fall behind. To make remote work an effective tool for economic and rural development, it would need to be complemented by local

skill-building, infrastructure investment, and labour market programmes.

Introduction

The Covid-19 pandemic has made remote work the 'new normal' form of organisation for many white collar employees. Pre-covid, only the most flexible employers allowed employees to work at a distance. The coordination costs of managing remote teams were considered too high [1]. In forcing office employees to work from home, the pandemic has vastly accelerated the adoption of digital technologies [2] and organisational adjustments that allow business processes to operate productively at a distance [3].

Organisations can realise substantial cost savings and tap into global talent pools if they adopt remote working practices and start to outsource business processes to the remote workforce [4]. But what are the consequences of remote working for the global division of labour? Here, we investigate the global geographies of a fully remote labour market — a so-called online labour platform — that provides the digital infrastructure to hire remote workers on demand. These online platforms have been established over the past 10 to 15 years and they allow even small companies or individual employers to outsource knowledge work to individual freelancers [5]. Due to the digital organisation of the hiring and work process on the platform, online labour markets can be considered as a prototype of a fully remote labour market. Having started as niche marketplaces for IT freelancers, these platforms now cover the whole spectrum of knowledge work, from data entry to management consulting, with millions of platform workers involved globally [6–8], and rising adoption during the Covid-19 pandemic [9]. The platform labour market has in fact seen substantial growth in recent years. According to Kassi et al. (2021) the number of globally registered online workers was 163 million in 2021 [6]. With the decade-long shift towards remote work [10] that has only been accelerated by the pandemic, more of the overall labour market could begin to resemble the online labour market soon.

Remote work organised via online platforms could bring jobs to workers from all over the globe [11–13]. In doing so, remote work could help to mitigate the global imbalance between the increasing supply of, and competition between, highly educated graduates in Global South and Global North countries — a phenomenon which has been described as the 'Global Auction' [14] — and the high global demand for talent. In bringing jobs and income to people in countries across the world and, in particular, in rural areas, remote work could help to foster more resilient, sustainable local communities [15, 16] and offer alternatives to the physical migration to places with more jobs and higher wage levels [17], if platform work can provide sustainable sources of income. However, several studies have reported that remote platform work is shaped by geographical frictions and biases that restrict participation, for example, time-zone differences, language-based communication difficulties, domestic and ethnic connections, or information asymmetries [18–21]. Similar to other complex economic activities such as research, innovation and industry [22] remote platform work might cluster in large cities. In the global remote labour market, modularisation of tasks and competitive dynamics could cause uneven geographical participation rates [23], bad working conditions [24–26], and precariousness for workers [27–29]; a process that has been subsumed under the term 'Digital Taylorism' [30]. Overall, the individual contributions provide coherent, but

62 fragmented perspectives on the phenomenon of remote platform work. The body of previous con-
63 tributions in sum, however, does not provide a comprehensive and stringent picture with respect
64 to the global geography of remote platform work and its' impact on the relationship between urban
65 and rural areas. One reason for this is a lack of sufficiently granular data.

66 Here, we examine the global geography of remote freelance work mediated by online labour
67 platforms empirically based on a data set covering 1.8 million remote jobs from 2013 to 2020 to
68 show that remote platform work mirrors the geographical and skill-based polarisation of labour
69 markets at large [31]. The data comes from one platform, which is among the largest in terms of
70 global market shares [8, 32]. In the discussion section, we consider what implications our findings
71 may have for remote platform work more generally and other types of remote work, including
72 regular employment performed remotely over the Internet.

73 In mapping the platform jobs to sub-national geographies in 139 countries and an established
74 occupation taxonomy, we reveal that the remote labour market is polarised along three dimensions:
75 globally between countries, between urban and rural areas within countries, and, overall, between
76 occupations and skill-sets. We relate the spatial and occupational variation to differences in the
77 global distribution of infrastructure, economic opportunities, and human capital. The data suggest
78 that agglomerative forces shape the global geography of remote work. These forces pull the most
79 profitable remote jobs to metropolitan areas and locations with existing competitive advantages
80 in information and communication technologies. At the same time, rural areas and disadvantaged
81 regions, particularly in Global South countries, are not able to attract many remote jobs. Urban
82 specialists can realise a premium for scarce skills [33], while less specialised remote platform workers
83 compete for low-wage jobs.

84 Based on these findings we argue that the global distribution of skills and enabling institutions
85 are the focal point of remote work. In this perspective, Digital Taylorism — the standardisation
86 and modularisation of complex production processes of the knowledge economy broken down
87 into simple and codified tasks together with improved monitoring capabilities [27] — is the very
88 process that makes remote work and global digital value chains possible [14]. Enabling cost
89 savings and access to talent pools simultaneously, Digital Taylorism is considered as the driver of
90 the specialisation and global integration of the digital workforce via remote work. This process
91 affects incomes and opportunities of knowledge work globally.

92 According to this reading of the empirical findings, we provide the following interpretation of
93 the global geography of platform work. Skill-biased technological change [34–36] allows people with
94 advanced digital skills (e.g. Data Scientists) to realise a premium from increased demand, while
95 offshoring, computerisation, and global competition for jobs that require less specialised knowledge
96 (e.g. Data Entry) drive wages downwards [37, 38]. The result is a polarised global market for
97 knowledge work [39] with its' geography stratified along the lines of the unequal distribution of
98 human capital. The antagonism between urban and rural areas — described by Paul Collier in his
99 book *The Future of Capitalism* as a deep dividing line between the 'booming metropolis' and the
100 'broken provincial city' [40] — plays out fully in the remote labour market. This is because the
101 institutions that enable a successful participation — access to knowledge building, training and
102 professional networks — concentrate in urban environments. Rural regions are less able to offer
103 specialised work opportunities and urban lifestyle [41, 42]. In contrast, in metropolitan areas, a
104 highly specialised local economy creates an abundance of opportunities to maintain a tech-savvy

105 'creative class' [43, 44]. The most profitable remote jobs require specialised IT-skills and go there-
 106 fore to metropolitan areas. The polarising forces that pull remote jobs to centres of economic
 107 activity with existing competitive advantages and digital infrastructures work almost unrestricted
 108 in the platform economy. This is because there are only limited frictions of geographical bound-
 109 aries, labour market regulations or formal entry barriers, which increase the role of information
 110 asymmetries, uncertainties, trust cues, and reputation systems in online labour markets [45–47].

111 In summary, our main argument is that the unequal global distribution of remote work is the
 112 result of the unbalanced distribution of skills, human capital, and opportunities across the globe
 113 [48, 49]. This uneven distribution of economic conditions and competitive advantages transcends
 114 to the platform economy and drives the geographical polarisation of the remote labour market.
 115 Remote workers with access to hard-to-copy skills can realise a substantial premium, while those
 116 who lack marketable, digital skills participate in a global rat race for remote jobs. Digitally enabled
 117 remote work will likely not disperse knowledge work more evenly across space but rather reinforce
 118 prevalent agglomerative dynamics.

119 Literature Review

120 In the following, we review the existing literature on (a) the relationship between digital tech-
 121 nologies and changing economic geographies, and (b) previous empirical approaches to measure
 122 platform work. The overview of the literature presented here is complemented by a more extensive
 123 literature review in the Supplementary Information (Appendix S3: SI section S3, in particular
 124 Tables S1 to S5). In the appendix, we also provide more context on definitions and the conceptu-
 125 alisation of the term 'remote platform work' (Appendix S2). Here, we focus on a brief discussion
 126 of common findings, data, methods, and limitations of previous work from which we derive the
 127 contribution of our study.

128 The economic geography of outsourcing, offshoring, and digital technolo- 129 gies

130 The rise and role of ICT technologies for (global) economic geographies is a subject of extensive
 131 scholarly work and debate. Through outsourcing, offshoring and task automation, ICT technolo-
 132 gies profoundly affect the location of economic activities and the global dynamics of interaction
 133 between economic centres. The internet has reduced frictions of economic interactions: low com-
 134 munication, transportation, and search costs, for example, enable more densely connected global
 135 value chains [50, 51].

136 Digital technologies facilitate the trade of commodities and in particular the trade of services
 137 at a distance. The offshoring of services allows for more complex global production networks [52]
 138 which further increase the international division of labour [53]. Several studies have attempted to
 139 capture the share and nature of jobs that could be offshored thanks to the increasing technological
 140 capabilities [34, 37, 38, 54]. While digital labour platforms are a relatively recent phenomenon,
 141 the offshoring of service activities has a long history. For example, in 1983, American Airlines
 142 established its first international back office in Barbados [55]. Paperwork was flown from the
 143 U.S., handled and digitised in Barbados and sent back electronically via satellite to save 50 per
 144 cent labour costs. In 2017, Feakins described how offshoring of services enabled complex global

145 economic relationships, such as the Off-offshoring of service tasks from Russia to Ukraine [56].

146 ICTs are also reshaping the distribution of economic activities within countries [50]. For
147 instance, Malecki (2002) observes that the geography of Internet backbone networks reinforces
148 urban-rural differences [57]. Despite considerable controversy, the evidence overall suggests that
149 the productivity impacts of ICTs are positive, but unevenly distributed [58, 59]. As a result,
150 urban centres are likely to benefit disproportionately from digital technologies, as they tend
151 to host specialised institutions and a more fine-grained division of labour than rural areas [22,
152 23, 60]. These are considered as enablers of complementary skills necessary to capitalise on the
153 opportunities of digital technologies [61, 62]. The same holds for the integration of Global South
154 countries into digital value chains. Overall, Hjort and Poulsen (2019) show that fast Internet
155 access correlates positively with employment rates in African countries, due to the technology’s
156 impact on firm entry, productivity, and exports [15]. However, for example, Foster et al. (2018)
157 find that East African firms involved in global value chains can only fully benefit from improved
158 internet connectivity if they have access to complementary capacities and competitive advantages.

159 In summary, the internet has profoundly affected the geography of economic activities within
160 and between countries across the globe over the past two to three decades. Overall, Information
161 and Communication Technologies in general and the internet in particular have supported more
162 fine-grained production chains and the offshoring of service activities. Online labour platforms
163 continue this trend: they could represent one avenue for the further integration of remote workers
164 into global digital value chains through outsourcing and offshoring. Studies from the platform
165 economy literature have researched the geography of this novel form of online mediated work. In
166 the following, we discuss the main findings and limitations of these studies with respect to the
167 geography of remote platform work and the role of skills, and we derive our study’s contribution
168 from there.

169 **The economic geography of platform work**

170 Empirical studies on the geography of platform work have mainly focused on (a) assessments of
171 the size of the platform labour market, (b) analyses of trade between countries, and (c) the role
172 of signalling mechanisms and skills.

173 The first overarching finding is that platform labour markets are growing in importance and
174 size [5, 13, 63] with estimated yearly growth rates of around 20 % [6, 8].

175 Secondly, studies have investigated international transactions in the platform labour market:
176 these are dominated by north-south interactions with employers from industrialised countries and
177 workers from less developed countries [12, 13, 21, 63, 64]. Despite its inclusive global digital infras-
178 tructure, several barriers to trade and sources of worker discrimination persist such as geographical
179 distance, language, time zone as well as cultural and ethical differences [13, 19–21, 64].

180 However, most of these studies use relatively small or old datasets, are limited to a small set
181 of countries or investigations on the country-level. For example, Horten et al. (2017) [13] focus
182 on the bilateral trade between countries in the online labour market with an economic gravity
183 model. Their investigation aims on statistically explaining the large share of US-Indian trade on
184 the online platform, and it stays largely on a descriptive level. Similarly, Agrawal et al. (2015)
185 [63] provide descriptive statistics about the development of wages in occupational groups and
186 selected countries over time, but do not explain the wage differences quantitatively. Lehdonvirta

et al. (2019) [5] theorise online labour platforms through transaction cost economics and test their hypotheses empirically with a data set of 10,000 projects in two countries. Borchert et al. (2018) [65] and Braesemann et al. (2022) [23] analyse the relationship between online labour participation and local economic conditions on a sub-national level, but their investigations are limited to only one country.

These examples highlight a limitation of previous empirical contributions on the geography of platform work: many studies used relatively small cross-section data sets and they treated countries as the smallest unit of geographical analysis. This impeded a thorough identification of the economic determinants that shape the geography of online labour markets between countries and sub-national regions on a global level.

A third stream of research has focused on the role of skills in remote platform work. These studies find that while skills are considered as an important predictor of wages, workers seem to have limited opportunities to learn and grow on online platforms [12, 27, 28, 65]. Skill certificates can increase worker earnings [32]. However, there is contradicting evidence about the role of reputation systems in building trust, ranging from having an inclusive effect benefiting workers from developing countries disproportionately [21] to reputation leading to increasing inequality (“super star effect”) [66]. Details of the platform design seems to play an important role.

In the studies on skills and signalling mechanisms, the operationalisation of skills represents a common challenge: many of the reviewed studies present simplistic operationalisations of skills or do not explicitly measure them at all. For example, Kässi and Lehdonvirta (2022) [32] focus on the wage effects of online workers obtaining skill certificates rather than on skill-based or occupational differences. Lehdonvirta et al. (2019) [5] compare only two occupations (writing vs. graphic design), similarly to Beerepoot and Lambregts (2015) [12] who operationalise differences in skill levels with only two occupations (web development = high skill vs. administrative support = low skill). Other studies focus more on reputation mechanisms than on skills or occupations as individual-level wage determinants [19, 66–68]. The network approach of Anderson (2017) [33] represents an exception. Anderson proposes a network-based method for measuring worker skills and finds that workers benefit from skill diversity.

In summary, while previous studies have investigated geographical and skill-related aspects of platform work, there is still a gap in the literature regarding the global distribution of online labour, and in particular its’ relation to the unequal global distribution of skills, human capital, and place-bound institutions. We extend the current literature on global geography of remote platform work by a quantitative analysis based on three relevant methodological advances: more and comprehensive data, geographic granularity, and matching of skills.

First, we collect one of the most extensive datasets on the subject, including almost 2 million projects spanning eight years from 2013–2020 and a fine-grained geographical granularity. Secondly, we take a global viewpoint including 139 countries while extending the analysis to the sub-national level. In particular, we map the geocoded online platform data to regional statistical data from the World Bank, the OECD and the Global Data Lab on the country- and sub-national level, which makes the global persistence of urban-rural differences visible for the first time. This step also allows for applying regression modelling to explain the geographical distribution in relation to local economic conditions and infrastructure. Thirdly, we propose a sound methodology to operationalise skills by matching remote jobs to a well-established occupational taxonomy. These

three methodological advances allow us to pose the following research questions:

RQ 1 How is remote platform work globally distributed between and within countries? What is the relationship between urban and rural areas?

RQ 2 Are the unequal global distributions of remote platform work activity and wage differentials in Global North and Global South countries determined by local institutions, infrastructure and economic conditions?

RQ 3 In how far are outcomes of different job types in the remote platform labour market (wage levels, value of experience) related to differences in competitive intensity and skill requirements across occupations?

Data and Methods

All the methods of the data collection and analysis are described in great detail in the Supporting Information (Appendices S 4 and S 5). Here, we summarise the most critical steps.

Data collection In this study, we combine three data sources: (a) transaction records from a globally leading online labour platform, (b) regional covariates covering the demography, economy and infrastructure in OECD+ and Global South countries, and (c) occupation statistics from the U. S. Bureau of Labour Statistics (Appendix S 4). The retrieval and assembly of online labour records proceeds in two steps: After having gathered information via the API about the projects of which we had IDs, we extracted the platform worker IDs from these projects. In total, we collected a data set of 1.8 million remote jobs from one global online labour platform covering eight years from 2013 to 2020.

Geocoding In a second step, we provided these IDs to the API to obtain the remaining information related to each transaction of these platform workers. This includes the hourly wage, the total price charged for the project, and the workers' country-city location (Appendix S 4: SI section S 4.1). Afterwards, we use a Geocoding API and provide it with a list of all unique country-city locations from both the employer and worker side of the platform transactions; a total of 66,085 locations (Appendix S 4: SI section S 4.2). Then, the geocoded online labour data is matched with national and sub-national statistics on demography, economy, and infrastructure. Here, three data sources are considered: World Bank for country-level statistics, OECD regional statistics for sub-national data in high and middle income countries from the Global North, and Global Data Lab for sub-national level data for low and middle income countries from the Global South (Appendix S 4: SI section S 4.3).

Occupation Mapping Besides the geographical analysis of online labour data, we also investigate the job types of the online projects. For this purpose, we match the online job categories with official occupational statistics used by the U. S. Bureau of Labour Statistics (BLS). The BLS provides detailed information about each occupation's educational requirements, skills, and abilities. This data is available via the Occupational Information Network O*NET (Appendix S 4: SI section S 4.4). To match online work descriptions with official occupational taxonomies, we use

the SOCCer (Standardized Occupation Coding for Computer-assisted Epidemiological Research) tool provided by the U. S. National Institutes of Health for an automatised coding of a sample of 345,000 online projects. We provide the online job category as job title, and the required skills and description of the online project as job description to the tool. Based on the occupational mapping, we derived two measures 1) capturing the skill or educational requirements of different occupations from BLS data and 2) the relevance of experience in obtaining online projects (Appendix S4: SI section S4.5). We present the distribution of skill requirements and use hierarchical cluster, applying a Euclidean distance measure and complete linkage as clustering method, to group skills and occupations. Furthermore, we relate occupation-level variables to the importance of experience in obtaining online projects. This is what we call the 'experience gradient'. The idea is that experience and reputation are known to drive outcomes in the platform economy, as they signal trustworthiness of sellers.

Regression Analysis Lastly, the regression analysis of the geographical distribution of online labour projects and wages relies on six regression models with multilevel effects, where we regress a broad set of regional characteristics on regional- and country-level wages and project count whilst ensuring accurate feature selection and out-of-sample prediction accuracy (Appendix S5), including various robustness checks to ensure that our findings are consistent across time and space (Appendix S6).

Results

Polarisation across space

Considering Research Question 1 on the global distribution of remote platform work, the data shows that the online labour market connects global demand for and supply of remote knowledge work (Fig. 1). However, while it is theoretically open to users from all over the world, Figure 1A shows that demand and supply highly cluster in a limited number of places. Most demand comes from urban areas in North America, West Europe, and Australia; most remote platform workers are located in East Europe, South Asia, and the Philippines. Dense flows of capital and labour connect these regions, while many Global South countries only marginally participate in the remote labour market. The overall polarisation remains largely persistent over time (Appendix S6: SI section S6.5).

The global differences in participation become more pronounced when considering the number of projects per capita (Fig. 1B). Online labour project count per population varies by several orders of magnitude within and between macro-regions (position of the dots on the y-axis): while almost all countries in Europe and North America hosted at least ten projects per one million population in 2020, only half of the countries in South & Central Asia, one-third in East Asia & Pacific, and 15 % in Sub-Saharan Africa did so. In absolute numbers (size of the dots), more than 50 % of all online labour projects were conducted by platform workers from just five countries (India, Pakistan, Philippines, United States, Bangladesh). Hourly wages (colour of the dots) also vary substantially: while platform workers in the United States, United Kingdom, and Russia charged more than 30 USD per hour on average, remote workers in Bangladesh and the Philippines earned just a fifth, or 6 USD an hour. There are also exceptions: for example, Kenya and South Africa host

relatively active platform worker communities. Kenya’s participation per population is comparable to that of the United States. Average wages of South Africa’s platform workers are comparable to those in Europe.

Inequalities between countries online labour activity have been reported in the past [13, 63]. However, here we also reveal the sub-national concentration of remote platform work globally (For more details, see Appendix S6: SI section S6.3.). Participation rates vary by two to four orders of magnitude in many countries (Fig. 1C), and the distribution within and between countries is highly concentrated, both in OECD + BRIICS (OECD countries and Brazil, Russia, India, Indonesia, China, and South Africa, abbreviated as OECD+). and Global South countries (Appendix S6: Fig. S17). In many countries, the capital region attracts most platform jobs in absolute and per capita terms (Fig. 1C), particularly in the Global South. In the OECD+, the capital regions attract more than three times as many platform jobs per capita than other regions in the same country on average. In the Global South, capital regions obtain more than 15 times as many projects per capita as other regions in the same country. On a global scale, platform work is a metropolitan phenomenon.

Additionally, hourly wages vary substantially between metropolitan and other regions. On average, platform workers in OECD+ capital regions earned 24 % more per hour than their counterparts in other regions. The wage spread was almost twice as high in Global South countries: platform workers in capital regions earned 53 % more than those in other regions.

Summarising the findings related to Research Question 1, the data suggest two dimensions of geographical polarisation in the global remote labour market. First, we find pronounced inequalities between countries worldwide along a North-South dimension. Most online labour demand comes from high-income countries. Supply comes mainly from platform workers in traditional outsourcing destinations in South Asia, the Philippines, and by platform workers from Europe and North America. Secondly, we identify persistent inequalities within countries. This points towards urban-rural differences as the second main polarisation dimension in the remote labour market. Platform workers in large cities and places with enabling institutions seem to be able to secure more and better paid jobs than their counterparts in rural regions.

Turning to Research Question 2, we find that regional factors explain the spatial polarisation described in Figure 1. Figure 2 shows six regression models relating the number of projects and hourly wages per country (models 1 and 4), per OECD+ region (models 2 and 5), and per Global South region (models 3 and 6) to country-level and sub-national covariates. Data sources are World Bank data (countries), the OECD regional database (sub-national regions OECD+), and the Global Data Lab [69] (sub-national regions Global South). The data covers the years 2013–2020 (for details on the data set and pre-processing, see Appendix S4: SI sections S4.1–S4.3 and Appendix S5: S5.1). In summary, the regression models contain data of 139 countries and 597 sub-national regions over eight years.

The dependent variable in the models (1) to (3) is inverse hyperbolic sine (ihs) transformed ($y = \log(x + \sqrt{x^2 + 1})$, see [70]) to reduce the skewness of the distribution, which ranges across several orders of magnitude. Hourly wages also vary substantially. Therefore, we also applied the ihs-transformation to the dependent variable in the models (4) to (6). As our models deal with different hierarchical levels (regions nested in countries or years), multi-level effects need to be

350 considered. We test and apply random and fixed effects to account for the variability of outcomes
351 within and across countries or years. (see Appendix S 5: SI section S 5.3).

352 To model the relation between the platform data and regional characteristics, we included
353 regional statistics commonly used in studies on the platform economy (see Appendix S 3, Appendix
354 S 4: S 4.3, and Appendix S 5: S 5.2).

355 The regression models (1) to (3) tell a coherent and robust story about the geography of
356 the platform labour market. The larger a region's population, the more projects it attracts.
357 Similarly, higher levels of education are associated with higher project counts. The income level
358 is negatively associated with project count on the global scale and in the OECD+, while it is
359 positively associated in Global South regions. This indicates that it is middle income countries or
360 regions, not the poorest places on earth, that attract most remote jobs. Internet connectivity is
361 positively associated with project count: the better the internet infrastructure, the more remote
362 platform work. The same holds the 'IT specialisation of the economy'. English language countries
363 attract more projects, as well as those that have a lower price level. In Global South regions, the
364 capital region indicator is strongly positively associated with activity.

365 The models (4) to (6) give insights into the factors that drive hourly wages. Overall, the
366 coefficients show a similar direction as in the models (1) to (3), with a few important exceptions.
367 For example, the English language coefficient is negative in model (4) because many high-wage
368 countries in Europe do not have English as an official language. The 'IT specialisation of the
369 economy' coefficient is negative in model (4). Income is positively associated on the country level
370 and the price level is not significant (potentially because platform workers in countries with higher
371 price levels tend to charge more). Education and internet connectivity are positively correlated
372 with hourly wages.

373 The regression models explain a large share of the total variation (see R^2 values in Fig 2A and
374 Fig 2B). Almost three-quarters of the total variance between countries (left panel of Fig 2B) can
375 be explained by the model: the residuals of very large players in the online labour market, such as
376 India, the United States, or Ukraine (red dots) are almost zero. Similarly, model 4 accounts for
377 44 % of global wage differentials (right panel of Fig. 2B).

378 In summary, we conclude that the global distribution of remote work seems to be constrained
379 by place-bound economic, infrastructure, and educational factors (RQ 2). The most profitable
380 projects are conducted in places with high human capital levels, specialised know-how, and a
381 robust local economy. Price differentials explain only a minor share of the global geography
382 (Appendix S 6: SI section S 6.2).

383 **Polarisation across skills**

384 To explain the wage differentials between job types in the platform labour market (Research
385 Question 3), we look into the skills related to the professions. Following the task-based approach
386 [34, 37, 71], we consider jobs as the manifestation of different tasks and skills. Figure 3A displays
387 the skill composition of each of the 46 occupations the platform job types can be grouped in (see
388 Appendix S 4: SI section S 4.4 for details on the matching between online job types and official
389 occupational categories). Skills (rows) and occupations (columns) are sorted by a hierarchical
390 clustering algorithm (see Appendix S 4: SI section S 4.5) to group occupations with similar skill
391 requirements, resulting in nine skill- and six occupation cluster.

The upper half of the heatmap reveals significant differences between the occupations. Job types in clusters 3 and 4 score heavily on computer-related skills; those in clusters 2 and 6 score most intensively on language and (written) communication skills. Occupations in clusters 1 and 5 score most heavily on oral communication or clerical tasks.

The varying skill requirements translate into different hourly wages (lower part of Fig. 3A). Jobs in clusters 3 and 4 pay an average wage of \$16–17, jobs in cluster 2 and 6 an average wage of \$15–16, and jobs in cluster 1 and 5 a mere average of \$6–9 per hour. In other words, skill sets determine wages. This is confirmed by two regression models in Figure 3B). Model (1) relates the average hourly wages per occupation to three variables: the average number of applicants per project (competitive intensity), the total number of projects per occupation (size of each occupational sub-market), and the educational attainment score (reflecting differences in required education levels, see Appendix S4: SI section S4.5). The model identifies a strong negative association between wages and competitive intensity. The educational attainment score is positively associated with wages, particularly for 'Non-Tech' occupations (see panel (i) and (ii) in Figure 3C).

For platform workers, expected wages are essential but not the only relevant outcome. Due to uncertainty in the remote labour market, workers need to send quality signals to demonstrate experience and trustworthiness to potential employers, such as ratings or reviews about past projects [67, 72]. Platform workers that can secure some initial projects to distinguish themselves from other, less experienced, competitors might be able to obtain more profitable projects in the future. To operationalise the varying importance of experience signals in different occupations, we developed a statistical measure of the relevance of past experience in obtaining additional projects: the *experience gradient*. We calculate the experience gradient per occupation as the slope parameter estimate $\hat{\beta}$ of a regression between the number of projects a platform worker in occupation i obtained in year t by the number of projects the same worker had conducted in previous years (see Appendix S4: SI section S4.5). The experience gradient is related to occupation-level variables in model (2) of Figure 3B. The model shows that competitive intensity, measured by the market size, and average wages are positively associated to the relevance of experience. This applies more strongly to Non-Tech jobs (panels (iii) and (iv) in Figure 3C): in more competitive occupations with less skill-based signalling options, experience is more relevant than in others.

Interpretation of the results

Here, we provide an interpretation of the quantitative findings regarding the spatial and skill-based polarisation or remote platform work. With respect to the geographical distribution (Research Questions 1 and 2), we argue that remote work does not simply flow to places with lower price levels, but that it is pulled towards locations with competitive advantages and a specialisation in information and communication technologies. This could be related to centripetal forces that characterise the spatial organisation of the institutions enabling remote knowledge work. These forces seem to be bigger than global price differentials, which could push remote work to places with low living costs. The places with the lowest price levels globally tend to not have a sufficient level of internet infrastructure, economic specialisation and know-how to enable workers to participate in the global market for remote knowledge work. The global polarisation in the remote labour

market is then a digital mirror of the global polarisation of skills and economic opportunities across the globe.

Considering the results with regards to the distribution of skills and wages in the online labour market, we conclude the following. First, in contrast to conventional labour markets, which are shaped by geographical and regulatory constraints leading to substantial wage differentials for similar types of jobs even in close geographical proximity—think of wage differentials at the US-Mexican border region, Hong Kong vs Mainland China, Switzerland vs adjacent European countries or South Europe vs North Africa—the remote platform labour market is truly global. It is, however, not just one market, but many: one market per occupation. The variation in hourly wages between occupations is larger than the overall variation between countries (Appendix S6: SI section S6.4).

Secondly, the regression models show that jobs with more applicants and less skill-based signalling pay lower wages (Research Question 3). We interpret this finding as follows: These occupations have low entry barriers and face more competition. Without skills as a quality signal, the number of prior projects or feedback scores becomes an entry barrier. Employers use trust cues to decide whom to hire from the large crowd of applicants. For platform workers, this could spark a race to the bottom: without reputation, they find it hard to get their first job, so they need to undercut wages, leading to a vicious circle of more competition and lower wages.

In contrast, people with in-demand skills can secure profitable projects and high wages. The skill-based polarisation does not work along a one-dimensional skill axis: for example, the highest paying occupation is 'Paralegals and Legal Assistants'. This occupation does not require an exceptionally high level of formal education, but knowledge of the legal system in the country of the employer (in many cases the United States). Similarly, 'Announcers' (i. e. audio online adverts etc.) receive high wages. This occupation comes with another hard-to-copy skill: an U.S. accent. In general, jobs with hard-to-acquire, technical skills show less competition and higher wages.

Overall, the findings lead to the conclusion that demand for and supply of skills drive outcomes in the remote labour market. The three axes of polarisation—global divides between countries, urban-rural imbalances within countries, and inequalities between occupations—reflect the scarcity and abundance of skills and the access to them. In the global platform labour market, the laws of supply and demand work unrestrained: individuals with in-demand skills are able to secure profitable jobs; others obtain low wages, face fierce competition, and reputation as a crucial entry barrier. The outcomes of individual platform workers are constrained by system-level mechanisms shaped by agglomerative forces, which are largely out of their hands. The jobs remote workers can perform online is then determined by their access to education, training, and specialised IT know-how. This access is linked to place-bound institutions of the local economy. If they are unlucky not to be located near specialised industries or agglomerations, they are more likely to offer work in occupations characterised by easy-to-copy skills and fierce competition. In contrast, remote workers from metropolitan areas already have access to ample urban opportunities for knowledge exchange and local work opportunities, due to a bundling of complex economic activities [22] and a more fine-grained division of labour in urban environments [60]. They will enjoy the increased global demand for IT and business services and attractive wages.

A Flows in the global online labour market between cities with majority buyers (blue) and sellers (red) in 2020 (5% sample)

B Distribution of 2020 country-level online labour project count per population in macro regions

C Distribution of 2020 region-level online labour project count per population within countries (red: capital region, blue: other regions)

Fig. 1 (A) Connections between majority buyer (blue) and seller cities (red) in the 2020 platform labour market (5% sample): hotspots of demand are North America, West Europe, and Australia; platform workers in Eastern Europe, South Asia and the Philippines conduct most remote jobs. **(B)** Distribution of 2020 online labour (OLM) project count per capita (y-axis) in countries (dots), grouped by global macro regions (x-axis): globally, platform activity varies by several orders of magnitude; Europe and North America show the highest levels of participation, and the highest average wages (dot colour); most countries in the Global South participate only marginally in the remote labour market with low wages and less than 10 projects per one million population, with the exception of the Philippines, Bangladesh, Pakistan, and India. **(C)** Online labour distribution within countries in OECD+ and Global South countries: participation varies vastly within countries with most capital regions (red) hosting the largest platform worker communities per country; the imbalance is particularly pronounced in the Global South where the capital region hosts, on average, 15-times as many projects per capita than other regions in the country.

A Regression models relating online labour project count (1-3) and avg. hourly wage (4-6) to regional covariates 2013 to 2020

Dependent variable:	Yearly online labour project count ^a			Online labour avg. wage per hour ^{a,b}		
Level:	Countries	Sub-national regions		Countries	Sub-national regions	
Geography:	Global	OECD+ ^c	Global South ^d	Global	OECD+ ^c	Global South ^d
Model:	(1)	(2)	(3)	(4)	(5)	(6)
Population	0.96***	0.85***	0.54***	0.04***	0.05	0.06***
Population, total (log scale)	(0.02)	(0.09)	(0.04)	(0.01)	(0.04)	(0.02)
Education	0.06***	0.004	0.07***	0.01***	0.01***	0.06***
Model (1), (4): share of pop. with secondary education	(0.003)	(0.01)	(0.03)	(0.001)	(0.002)	(0.02)
Model (2), (5): share of pop. with tertiary education						
Model (3), (6): avg. years of education						
Income per capita	-0.01***	-0.33***	0.06***	0.002***	-0.12***	0.03***
Model (1), (4): GDP per capita (in 1,000 \$)	(0.003)	(0.10)	(0.02)	(0.001)	(0.05)	(0.01)
Model (2), (5): GDP per capita (2015 PPP \$, log scale)						
Model (3), (6): Gross National Income p.c. (2011 PPP \$)						
Internet connectivity	0.04***	0.03***	0.02***	0.01***	0.005***	0.003**
Model (1), (4): fixed broadband subscriptions per 100 people	(0.01)	(0.004)	(0.004)	(0.002)	(0.001)	(0.001)
Model (2), (5): share of HHs with internet broadband access						
Model (3), (6): share of HHs with internet access						
IT specialisation of the economy	0.22***	0.56***		-0.02*	0.09***	
Model (1), (4): ICT share of all service exports (log scale)	(0.04)	(0.05)		(0.01)	(0.02)	
Model (2), (5): Gross value added in ICT (2015 PPP \$, log)						
English language	0.68***			-0.07**		
Indicator: English is official language	(0.11)			(0.03)		
Price level	-0.32***			-0.04		
PPP conversion factor (per 1,000 int. \$)	(0.08)			(0.02)		
Capital region		0.13	1.75***		-0.08**	-0.12**
Indicator: region holds country capital		(0.10)	(0.10)		(0.03)	(0.05)
Constant					3.21***	2.49***
					(0.31)	(0.12)
n (regional units)	139	292	305	112	253	56
Observations	1,136	2,384	2,122	763	1,536	255
Fixed / Random Effects	Yearly FE	Country-year Fixed Effects		Yearly FE	Country-year Random Effects	
R ²	0.72	0.70	0.43	0.44	0.79	0.69
Adjusted R ²	0.71	0.67	0.36	0.43	0.79	0.68

Note:

*p<0.1; **p<0.05; ***p<0.01

^aInverse hyperbolic sine (ihs) transformed: $y = \log(x + \sqrt{x^2 + 1})$.

^bTo ensure convergence of the mean wage, countries or regions with a project count of less than 25 have been excluded from the regression models (4)–(6).

^cRegions in OECD countries and Brazil, Russia, India, Indonesia, China, and South Africa.

^dRegions in Global South countries available in the *Global Data Lab* database.

B Spread of online labour project count (left panel) and average hourly wage (right panel) per country in 2020, compared to the spread of the residuals of the optimised models (1) and (4)

Fig. 2 (A) Regressions between online labour project count (models 1–3), avg. hourly wage (models 4–6) and regional covariates (2013–2020 data, in total 1.76 million projects): population, education, internet connectivity, and the IT specialisation of the economy are positively associated with project count and hourly wages; globally, countries with English language and low price levels are more active in the remote labour market. **(B)** Spread of online labour (OLM) project count (left panel) and avg. hourly wage (right panel) per country vs. residuals of the regression models (1) and (4): the parsimonious models explain large shares of the global variation; for example, the countries at both ends of the project and wage spectrum (highlighted in red) show substantially reduced residuals after controlling for regional covariates. Overall, the regression models explain between 42% and 79% of the variation between countries or regions.

A Heatmap of skill intensity per occupation (occupations clustered by skill similarity) and wage levels per cluster (lower panel)

Discussion

The Covid-19 pandemic has led to the rise of remote work. Digital technologies enable the practical organisation of work at a distance. The potential cost savings, more flexibility, and improved access to talent suggest that remote work is likely to play an essential role in the future of work. However, it is unclear how far remote work will influence the global division of labour. In particular, does remote work bring jobs to rural areas and disadvantaged regions or will it reinforce global spatial imbalances? To investigate this question quantitatively, we draw on data from a fully remote labour market: an online labour platform. In the empirical part of this study, we analyse remote work mediated by an online labour platform. Here, in the discussion section, we also consider what implications the quantitative findings may have for remote work more generally, including regular employment performed remotely over the internet.

On the platform, workers from all over the world can find and conduct jobs covering the whole spectrum of knowledge work. As the whole work process—from the job advert over the interview, onboarding, communication, to payment and dispute resolution—is conducted online, the platform labour market could provide an outlook into the future of work. This future might be shaped by more remote contracts [73, 74] and the platformisation of jobs [75–77].

The data suggest that agglomerative forces shape the global geography of remote work, leading to the following interpretation. Jobs are pulled to places with enabling institutions of remote work, which are unequally distributed across the globe. Complex economic activities and specialised vocational training concentrate in large cities [22, 42]. In having access to these opportunities and skills, the remote workforce in urban areas is able to obtain the most profitable remote jobs, while their counterparts outside of economic centres find it more difficult to offer in-demand skills on the global platform labour market. The unequal spatial distribution of skills, institutions, and opportunities determine the global geography of remote work. The dynamics of the platform economy amplify this process, as there are little geographical or regulatory boundaries on the online platform that would slow down the global competition.

Across countries, we observe a spatial division of work that resembles the offshoring rationale of business processes, which started in the 1980s and 1990s [4]. Increasingly modularised and standardised tasks within the ever-growing digital economy have enabled a fine-grained global division of knowledge work connecting North America, West Europe, and Australia with South Asia, the Philippines, and East Europe. This observation is in accordance with earlier work that investigated the increasingly globalised market for knowledge work and Digital Taylorism—the modularisation and standardisation of cognitive tasks together with a fine-grained division of these tasks across different job types in global digital value chains—such as ‘The Global Auction’ by Brown et al. (2010). However, the data shows that most countries in the Global South are only marginally connected to the global web of remote work in the platform labour market.

Within countries, we find that remote work flows to urban centres. These are the places where highly skilled labour is concentrated. The economic tale of the ‘booming metropolis’ and the ‘broken provincial city’ [40] plays out fully in the platform economy. This imbalance resembles existing opportunity gaps between urban and rural areas, which have pulled skilled workers to cities already before the rise of the platform economy. In fact, while online labour platforms are thought to offer an alternative to employment-based migration, constituting a form of ‘virtual migration’

517 [78], studies suggest that online labour platforms are frequently used by migrants [79]. Similarly,
518 online labour platforms are more intensively used by younger parts of the working age population.
519 Pajarinen et al. (2018) find that many online freelancers in Finland are less than 30 years old [79].
520 It is the young, talented part of the workforce that most likely migrates to urban areas because
521 of better income opportunities [80]. Such opportunity-based migration to metropolitan areas and
522 resulting differences in the age structure of urban and rural areas is probably one of the drivers
523 of the geographical disparities in the platform data. Overall, we observe that remote platform
524 workers in metropolitan areas are more likely to attract specialised online jobs and high wages.

525 The findings highlight the pivotal role of skills in driving remote work towards metropolitan
526 areas. Individual occupations form sub-markets of the global platform labour market. Platform
527 workers are constrained to work in those jobs that reflect their skills and experiences [81]. Com-
528 petitive pressure differs between job types as workers cannot freely move between occupations.
529 This leads to a scarcity premium in some occupations, while others suffer from low wages and
530 excess supply. In that situation, the uncertainties of the platform economy spark a race to the
531 bottom: feedback and prior work experience are highly relevant to obtain remote jobs [46, 82];
532 newcomers will find it hard to get their first job and might be forced to undercut wages. This fuels
533 competition and spirals wages downwards. Besides the intense competition and limited opportu-
534 nities for signalling work quality, which we describe in this study quantitatively, the literature has
535 discussed the role of algorithmic control [27, 83] and the organisation mechanisms of work in the
536 platform economy [30, 84] as drivers of (adverse) outcomes for remote platform workers.

537 Our analysis implies that agglomerative forces drive the polarisation of the remote labour
538 market. Market access alone will not lead to a less unequal division of labour. Remote workers
539 in disadvantaged areas need more than a computer and broadband internet alone to thrive. They
540 need to have marketable skills to make remote work a tool for rural and economic development.

541 **Policy Implications** Initiatives such as the Rockefeller Foundation’s *Digital Jobs Africa* or
542 Kenya’s *Ajira Digital* work programme aim to bring millions of remote jobs to Africa, but they
543 could make matters worse for remote workers: if they increase the supply in certain types of
544 occupations, they could fuel the competitive spiral of excess labour supply and pressure on wages.
545 To increase chances of remote workers in disadvantaged regions, retraining programmes need to
546 focus on in-demand skills and account for the quickly changing dynamics in the global market
547 for talent. It is unlikely that remote worker communities can thrive if there are limited local
548 opportunities. Therefore, online work programmes in rural areas—both in Global North and
549 Global South countries—should be embedded in larger economic and labour market development
550 schemes, which provide reliable internet access, local employment alternatives, and skill-building
551 opportunities. This applies also to remote labour demand. Remote platform work can be a chance
552 for rural employers to get access to global talent. Programmes that foster the integration of remote
553 work into their business processes might help companies to become more resilient and to keep them
554 in their local surrounding.

555 Online platform providers could increase the visibility of objective quality metrics, such as
556 educational degrees, to limit the adverse effects of reputational feedback loops in the remote plat-
557 form labour market. Platform apprenticeships for new remote workers—the random assignment
558 of first jobs to people without experience on the platform—could help to build up initial credibil-

ity [67] and lower entry barriers. Moreover, governmental organisations that aim to improve the working conditions of remote platform workers, such as the European Commission, could support the positive development of platform work in advertising short-term remote jobs directly on online platforms while promoting living wages. They could also help in developing and accrediting objective quality metrics. Another way to strengthen local communities of remote platform workers could be the support of coworking spaces and other forms of physical meeting points for platform workers. Such spaces could focus on providing workplaces with all the equipment and services necessary for performing remote jobs effectively. In bringing remote workers together and offering complementary services, these spaces could foster knowledge exchange and skill-building, and they could help remote platform workers to gain a sense of community.

Implications for the future of remote work Why is it that remote work is unlikely to change the economic imbalance between urban and rural areas majorly? Remote work allows people to move freely from urban to rural areas only in the short term. Some urban specialists might enjoy the new remote work opportunities and relocate to suburban or rural environments, substituting day-to-day commutes with digital interactions. They can stay connected to their peers in urban centres via video calls, but they will find it difficult to establish new links and access informal knowledge exchange through local networks.

In contrast, the city, as a hub of interaction supports specialised local jobs and occupational diversity [60, 85, 86]. An increasing share of complex economic activities [22], and non-linear scaling laws make the provision of specialised occupations more sustainable in large agglomerations [87–89]. This will likely continue to pull business opportunities and people towards cities. Digital technologies and organisational adjustments during the Covid pandemic have enabled seamless communication and collaboration over distance, which theoretically allows for a wide-spread web of economic and labour market interactions between urban and rural environments. Still, the network forces that pull innovation and business opportunities towards large agglomerations are likely to also shape the global geography of remote work. In the remote labour market, the place of work might not be limited to the same city anymore. But instead of dispersing more equally across space, remote work probably tends to cluster in metropolitan areas in different parts of the world, which share similar institutions and urban lifestyle that enable knowledge work to flourish locally.

Limitations Our study comes with some methodological limitations. The data collection (described in Appendix S4) depends on access to the online platform’s API. We cannot make claims about the size of our sample in relation to the overall size of the remote platform labour market, but we are confident that sampling issues did not bias the analysis. This is because our findings are robust over all the years in the sample and they align with previous investigations on the geography of platform work. Furthermore, Our study analyses data from only one platform, but the platform investigated here is one of the global market leaders. In the data analysis, we had to make simplifying assumptions: in mapping the platform job categories to the official occupation taxonomy, we had to disregard the multifaceted skill-dimensionality of jobs within each occupation. Moreover, the algorithmic geocoding and occupation mapping come with some uncertainties. However, we very carefully investigated each step of the data preparation for potential

errors (outlined in the SI) and we performed several robustness checks (for example, Appendix S 6: SI section S 6.1) to validate parameter choices.

Conclusion

Remote work mirrors the spatial inequalities of labour markets at large. The most profitable jobs are pulled towards the booming tech-savvy metropolis, while rural areas fall behind. In contrast to on-site labour markets, the polarisation mechanisms are amplified in the platform economy, as the forces of supply and demand are fully unleashed in the absence of regulatory barriers.

The unequal spatial distribution of institutions enabling skill-building and business opportunities determine the geography of the remote labour market. While internet connectivity and price differentials channel remote work around the globe, only remote workers with access to specialised skills attract valuable projects. Platform reputation mechanisms further accelerate the global race to the bottom for those who do not possess in-demand skills. Still, remote work can become an instrument of economic empowerment and growth. For this to happen, remote work needs to be embedded in broader economic and labour market development schemes, supporting disadvantaged regions to invest in local skill development and infrastructure.

Only in regions that flourish locally, remote workers can succeed globally.

Supporting Information

Supporting Information. This document contains additional information on the manuscript containing the following elements: *Overview and structure of the supporting information.* This part of the Supporting Information provides an overview of all additional materials and information provided in the appendix. *Conceptualising Remote Platform Work.* This element of the appendix discusses different definitions, interpretations and conceptualisations of remote platform work. We place the platform we investigate in the empirical part of the study in that classification. *Empirical approaches to measure platform work.* Here, we provide a tabular overview of the the main findings from the empirical literature related to our work, i. e. studies that measured the geography and role of skills in platform work. *Data collection and processing.* This part of the appendix provides all the details necessary to replicate the data collection and pre-processing of the data prior to analysis, including the collection and preparation of the online platform data, the regional statistical data, and occupation data; geocoding; and the derivation of occupation-level measures from the data. *Regression analysis of geographical polarisation.* Here, we outline the preparatory steps undertaken before conducting the regression analysis. In particular, we provide information about transformations and descriptive statistics about the output and explanatory features, and we discuss the choice of the final model specification used in the regression analysis. *Additional analyses.* This section presents robustness checks and further analyses. We investigate the robustness of the results with regard to the imputation of missing variables, analyse the model residuals, discuss the spatial granularity of the data, compare the wage distribution across countries and occupations, and we analyse the spatial polarisation over time.

References

- [1] Chris Forman and Nicolas van Zeebroeck. From wires to partners: How the internet has fostered r&d collaborations within firms. *Management science*, 58(8):1549–1568, 2012.
- [2] Joel B Carnevale and Isabella Hatak. Employee adjustment and well-being in the era of covid-19: Implications for human resource management. *Journal of Business Research*, 116:183–187, 2020.
- [3] Brodie Boland, Aaron De Smet, Rob Palter, and Aditya Sanghvi. Reimagining the office and work life after covid-19. White paper, McKinsey, 2020.
- [4] Stephan Manning, Marcus M. Larsen, and Chacko G. Kannothra. Global Sourcing of Business Processes. In *The New Oxford Handbook of Economic Geography*, pages 407–426. Oxford University Press, 2018.
- [5] Vili Lehdonvirta, Otto Kässi, Isis Hjorth, Helena Barnard, and Mark Graham. The global platform economy: A new offshoring institution enabling emerging-economy microproviders. *Journal of Management*, 45(2):567–599, 2019.
- [6] Otto Kässi, Vili Lehdonvirta, and Fabian Stephany. How many online workers are there in the world? a data-driven assessment [version 2; peer review: 3 approved. 2021.
- [7] Richard Heeks. Decent Work and the Digital Gig Economy. Development Informatics Working Paper 71, SSRN, 2017.
- [8] Otto Kässi and Vili Lehdonvirta. Online labour index: Measuring the online gig economy for policy and research. *Technological forecasting and social change*, 137:241–248, 2018.
- [9] Fabian Stephany, Michael Dunn, Steven Sawyer, and Vili Lehdonvirta. Distancing bonus or downscaling loss? the changing livelihood of us online workers in times of covid-19. *Tijdschrift voor economische en sociale geografie*, 111(3):561–573, 2020.
- [10] Beverly Yuen Thompson. The digital nomad lifestyle:(remote) work/leisure balance, privilege, and constructed community. *International Journal of the Sociology of Leisure*, 2(1):27–42, 2019.
- [11] James Manyika, Susan Lund, Kelsey Robinson, John Valentino, and Richard Dobbs. A labor market that works: Connecting talent with opportunity in the digital age. Working paper, McKinsey Global Institute, 2015.
- [12] Niels Beerepoot and Bart Lambregts. Competition in online job marketplaces: towards a global labour market for outsourcing services? *Global Networks*, 15(2):236–255, 2015.
- [13] John Horton, William R. Kerr, and Christopher Stanton. High-skilled migration to the united states and its economic consequences. In Gordon H. Hanson, William R. Kerr, and Sarah Turner, editors, *High-Skilled Migration to the United States and Its Economic Consequences*, chapter 3, pages 71–108. University of Chicago Press, 2018.
- [14] Phillip Brown, Hugh Lauder, and David Ashton. *The global auction: The broken promises of education, jobs, and incomes*. Oxford University Press, 2010.
- [15] Jonas Hjort and Jonas Poulsen. The arrival of fast internet and employment in africa. *American Economic Review*, 109(3):1032–79, 2019.
- [16] James Manyika, Armando Cabral, Lohini Moodley, Suraj Moraje, Safroadu Yeboah-Amankwah, Michael Chui, and Jerry Anthonyrajah. Lions go digital: The Internet’s transformative potential in Africa. Technical report, McKinsey Global Institute, 2013.
- [17] Kati Suominen. Fuelling Trade in the Digital Era. Issue Paper, International Centre for Trade and Sustainable Development, Geneva, 2017.
- [18] Vili Lehdonvirta, Helena Barnard, Mark Graham, and Isis Hjorth. Online labour markets-levelling the playing field for international service markets? Conference paper, Oxford Internet Institute, 2014.
- [19] Yili Hong and Paul A Pavlou. On buyer selection of service providers in online outsourcing platforms for it services. *Information Systems Research*, 28(3):547–562, 2017.
- [20] Ejaz Ghani, William R Kerr, and Christopher Stanton. Diasporas and outsourcing: evidence from odesk and india. *Management Science*, 60(7):1677–1697, 2014.
- [21] Ajay Agrawal, Nicola Lacetera, and Elizabeth Lyons. Does standardized information in online markets disproportionately benefit job applicants from less developed countries? *Journal of international Economics*, 103: 1–12, 2016.

- [22] Pierre-Alexandre Balland, Cristian Jara-Figueroa, Sergio G Petralia, Mathieu PA Steijn, David L Rigby, and César A Hidalgo. Complex economic activities concentrate in large cities. *Nature Human Behaviour*, 4(3): 248–254, 2020.
- [23] Fabian Braesemann, Vili Lehdonvirta, and Otto Kässi. Icts and the urban-rural divide: can online labour platforms bridge the gap? *Information, Communication & Society*, 25(1):34–54, 2022.
- [24] Mark Graham and Mohammad Amir Anwar. The global gig economy: Towards a planetary labour market? *First Monday*, 24(4), 2019.
- [25] Mark Anner, Nicolas Pons-Vignon, and Uma Rani. For a future of work with dignity: A critique of the world bank development report, the changing nature of work. *Global Labour Journal*, 10(1), 2019.
- [26] Richard W Mallett. Seeing the "changing nature of work" through a precarity lens. *Global Labour Journal*, 11(3), 2020.
- [27] Alex J Wood, Mark Graham, Vili Lehdonvirta, and Isis Hjorth. Good gig, bad gig: Autonomy and algorithmic control in the global gig economy. *Work, Employment and Society*, 33(1):56–75, 2019.
- [28] Uma Rani and Marianne Furrer. On-demand digital economy: Can experience ensure work and income security for microtask workers? *Jahrbücher für Nationalökonomie und Statistik*, 239(3):565–597, 2019.
- [29] Mark Graham, Isis Hjorth, and Vili Lehdonvirta. Digital labour and development: impacts of global digital labour platforms and the gig economy on worker livelihoods. *Transfer: European review of labour and research*, 23(2):135–162, 2017.
- [30] Mohammad Amir Anwar and Mark Graham. Hidden transcripts of the gig economy: labour agency and the new art of resistance among african gig workers. *Environment and Planning A: Economy and Space*, 52(7): 1269–1291, 2020.
- [31] H David, Lawrence F Katz, and Melissa S Kearney. The polarization of the us labor market. *American economic review*, 96(2):189–194, 2006.
- [32] Otto Kässi and Vili Lehdonvirta. Do microcredentials help new workers enter the market? evidence from an online labor platform. *Journal of Human Resources*, pages 0519–10226R3, 2022.
- [33] Katharine A. Anderson. Skill networks and measures of complex human capital. *Proceedings of the National Academy of Sciences*, 2017.
- [34] David H. Autor, Frank Levy, and Richard J. Murnane. The skill content of recent technological change: An empirical exploration. *The Quarterly journal of economics*, 118(4):1279–1333, 2003.
- [35] Daron Acemoglu and David Autor. Skills, tasks and technologies: Implications for employment and earnings. In *Handbook of labor economics*, volume 4, pages 1043–1171. Elsevier, 2011.
- [36] Maarten Goos, Alan Manning, and Anna Salomons. Explaining job polarization: Routine-biased technological change and offshoring. *American economic review*, 104(8):2509–26, 2014.
- [37] Carl Benedikt Frey and Michael A. Osborne. The future of employment: how susceptible are jobs to computerisation? *Technological forecasting and social change*, 114:254–280, 2017.
- [38] Alan S. Blinder. How many US jobs might be offshorable? *World Economics*, 10(2):41, 2009.
- [39] H David and David Dorn. The growth of low-skill service jobs and the polarization of the us labor market. *American Economic Review*, 103(5):1553–97, 2013.
- [40] Paul Collier. *The future of capitalism: Facing the new anxieties*. Penguin UK, 2018.
- [41] Amy K Glasmeier. Income inequality and growing disparity: Spatial patterns of inequality and the case of the usa. *The new Oxford handbook of economic geography*, page 63, 2018.
- [42] Luís MA Bettencourt, Horacio Samaniego, and Hyejin Youn. Professional diversity and the productivity of cities. *Scientific reports*, 4(1):1–6, 2014.
- [43] Richard L Florida et al. *Cities and the creative class*. Psychology Press, 2005.
- [44] Ron A Boschma and Michael Fritsch. Creative class and regional growth: Empirical evidence from seven european countries. *Economic geography*, 85(4):391–423, 2009.
- [45] Alan Benson, Aaron Sojourner, and Akhmed Umyarov. Can reputation discipline the gig economy? experimental evidence from an online labor market. *Management Science*, 66(5):1802–1825, 2020.

- [46] John J Horton. Buyer uncertainty about seller capacity: Causes, consequences, and a partial solution. *Management Science*, 65(8):3518–3540, 2019.
- [47] Moshe A Barach, Joseph M Golden, and John J Horton. Steering in online markets: the role of platform incentives and credibility. *Management Science*, 66(9):4047–4070, 2020.
- [48] Diane Perrons. Understanding social and spatial divisions in the new economy: New media clusters and the digital divide. *Economic geography*, 80(1):45–61, 2004.
- [49] Ian Richard Gordon and Ioannis Kaplanis. Accounting for big-city growth in low-paid occupations: Immigration and/or service-class consumption. *Economic Geography*, 90(1):67–90, 2014.
- [50] Chris Forman, Avi Goldfarb, and Shane Greenstein. How Geography Shapes - and is Shaped by - the Internet. In *The New Oxford Handbook of Economic Geography*, pages 269–285. Oxford University Press, 2018.
- [51] Mark Graham. Warped geographies of development: The Internet and theories of economic development. *Geography compass*, 2(3):771–789, 2008.
- [52] Henry Wai-Chung Yeung. The Logic of Production Networks. In *The New Oxford Handbook of Economic Geography*, pages 382–406. Oxford University Press, 2018.
- [53] Johannes M. Bauer. The Internet and income inequality: Socio-economic challenges in a hyperconnected society. *Telecommunications Policy*, 42(4):333–343, 2018.
- [54] Alan S. Blinder and Alan B. Krueger. Alternative measures of offshorability: a survey approach. *Journal of Labor Economics*, 31(S1):S97–S128, 2013.
- [55] Stephan Manning, Marcus M. Larsen, and Chacko G. Kannothra. Global sourcing of business processes: History, effects, and future trends. *The new Oxford handbook of economic geography*, pages 407–435, 2017. Publisher: Oxford University Press Oxford.
- [56] Melanie Feakins. Off-offshoring from russia to ukraine: How russian transnational entrepreneurs created a post-soviet it offshore. *Economic Geography*, 93(4):397–417, 2017.
- [57] Edward J Malecki. The economic geography of the internet’s infrastructure. *Economic geography*, 78(4):399–424, 2002.
- [58] Khuong Vu, Payam Hanafizadeh, and Erik Bohlin. Ict as a driver of economic growth: A survey of the literature and directions for future research. *Telecommunications Policy*, 44(2):101922, 2020.
- [59] Carol Corrado and Bart van Ark. The internet and productivity. In *Handbook on the Economics of the Internet*. Edward Elgar Publishing, 2016.
- [60] Luís MA Bettencourt, Horacio Samaniego, and Hyejin Youn. Professional diversity and the productivity of cities. *Scientific reports*, 4:5393, 2014.
- [61] Roberto Gallardo, Brian Whitacre, Indraneel Kumar, and Sreedhar Upendram. Broadband metrics and job productivity: a look at county-level data. *The Annals of Regional Science*, 66(1):161–184, 2021.
- [62] Dario Diodato, Frank Neffke, and Neave O’Clery. Why do industries coagglomerate? how marshallian externalities differ by industry and have evolved over time. *Journal of Urban Economics*, 106:1–26, 2018.
- [63] Ajay Agrawal, John Horton, Nicola Lacetera, and Elizabeth Lyons. Digitization and the contract labor market: A research agenda. In *Economic analysis of the digital economy*, pages 219–250. University of Chicago Press, 2015.
- [64] Vili Lehdonvirta and Greetje Corporaal. Platform Sourcing: How Fortune 500 Firms are Adopting Online Freelancing Platforms. *Oxford Internet Institute*, 2017.
- [65] Kathrin Borchert, Matthias Hirth, Michael E Kummer, Ulrich Laitenberger, Olga Slivko, and Steffen Viete. Unemployment and online labor. *ZEW-Centre for European Economic Research Discussion Paper*, (18-023), 2018.
- [66] Martin Lukac and André Grow. Reputation systems and recruitment in online labor markets: insights from an agent-based model. *Journal of Computational Social Science*, 4(1):207–229, 2021.
- [67] Amanda Pallais. Inefficient hiring in entry-level labor markets. *American Economic Review*, 104(11):3565–99, 2014.
- [68] Christopher T Stanton and Catherine Thomas. Landing the first job: The value of intermediaries in online hiring. *The Review of Economic Studies*, 83(2):810–854, 2016.

- [69] Jeroen Smits. GDL Area Database. GDL Working Paper 16-101, Global Data Lab, Institute for Management Research, Radboud University, 2016.
- [70] John B. Burbidge, Lonnie Magee, and A. Leslie Robb. Alternative Transformations to Handle Extreme Values of the Dependent Variable. *Journal of the American Statistical Association*, 83(401):123–127, 1988.
- [71] Emil Mihaylov and Kea Gartje Tjzens. Measuring the routine and non-routine task content of 427 four-digit isco-08 occupations. Working paper, SSRN, 2019.
- [72] Amanda Pallais and Emily Glassberg Sands. Why the referential treatment? Evidence from field experiments on referrals. *Journal of Political Economy*, 124(6):1793–1828, 2016.
- [73] Adam Ozimek. The future of remote work. *Available at SSRN 3638597*, 2020.
- [74] Jose Maria Barrero, Nicholas Bloom, and Steven J Davis. Why working from home will stick. Technical report, National Bureau of Economic Research, 2021.
- [75] Christina Behrendt, Quynh Anh Nguyen, and Uma Rani. Social protection systems and the future of work: Ensuring social security for digital platform workers. *International Social Security Review*, 72(3):17–41, 2019.
- [76] Aniket Kittur, Jeffrey V Nickerson, Michael Bernstein, Elizabeth Gerber, Aaron Shaw, John Zimmerman, Matt Lease, and John Horton. The future of crowd work. In *Proceedings of the 2013 conference on Computer supported cooperative work*, pages 1301–1318, 2013.
- [77] Werner Eichhorst, Holger Hinte, Ulf Rinne, and Verena Tobsch. How big is the gig? assessing the preliminary evidence on the effects of digitalization on the labor market. *Management revue*, pages 298–318, 2017.
- [78] Panagiotis G Ipeirotis and John J Horton. The need for standardization in crowdsourcing. In *Proceedings of the workshop on crowdsourcing and human computation at CHI*, 2011.
- [79] Mika Pajarinen, Petri Rouvinen, Jörg Claussen, Jari Hakanen, Anne Kovalainen, Tobias Kretschmer, Seppo Poutanen, Mareike Seifried, and Laura Seppänen. Upworkers in finland: Survey results. Technical report, ETLA Report, 2018.
- [80] Alwyn Young. Inequality, the urban-rural gap, and migration. *The Quarterly Journal of Economics*, 128(4):1727–1785, 2013.
- [81] Martin Lukac. Two worlds of online labour markets: Exploring segmentation using finite mixture models and a network of skill co-occurrence. Working paper, SocArXiv, 2021.
- [82] Mingfeng Lin, Yong Liu, and Siva Viswanathan. Effectiveness of reputation in contracting for customized production: Evidence from online labor markets. *Management Science*, 64(1):345–359, 2018.
- [83] David Stark and Ivana Pais. Algorithmic management in the platform economy. *Sociologica*, 14(3):47–72, 2020.
- [84] Mareike Möhlmann, Lior Zalmanson, Ola Henfridsson, and Robert Wayne Gregory. Algorithmic management of work on online labor platforms: When matching meets control. *MIS Quarterly*, 45(4), 2021.
- [85] Leo Sveikauskas. The productivity of cities. *The Quarterly Journal of Economics*, 89(3):393–413, 1975.
- [86] John M. Quigley. Urban diversity and economic growth. *Journal of Economic perspectives*, 12(2):127–138, 1998.
- [87] Luís MA Bettencourt. The origins of scaling in cities. *science*, 340(6139):1438–1441, 2013.
- [88] Luís MA Bettencourt, José Lobo, Dirk Helbing, Christian Kühnert, and Geoffrey B West. Growth, innovation, scaling, and the pace of life in cities. *Proceedings of the national academy of sciences*, 104(17):7301–7306, 2007.
- [89] Luís MA Bettencourt, José Lobo, Deborah Strumsky, and Geoffrey B West. Urban scaling and its deviations: Revealing the structure of wealth, innovation and crime across cities. *PloS one*, 5(11):e13541, 2010.