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Trade, competition and welfare in global online labour markets: A "gig economy" case study

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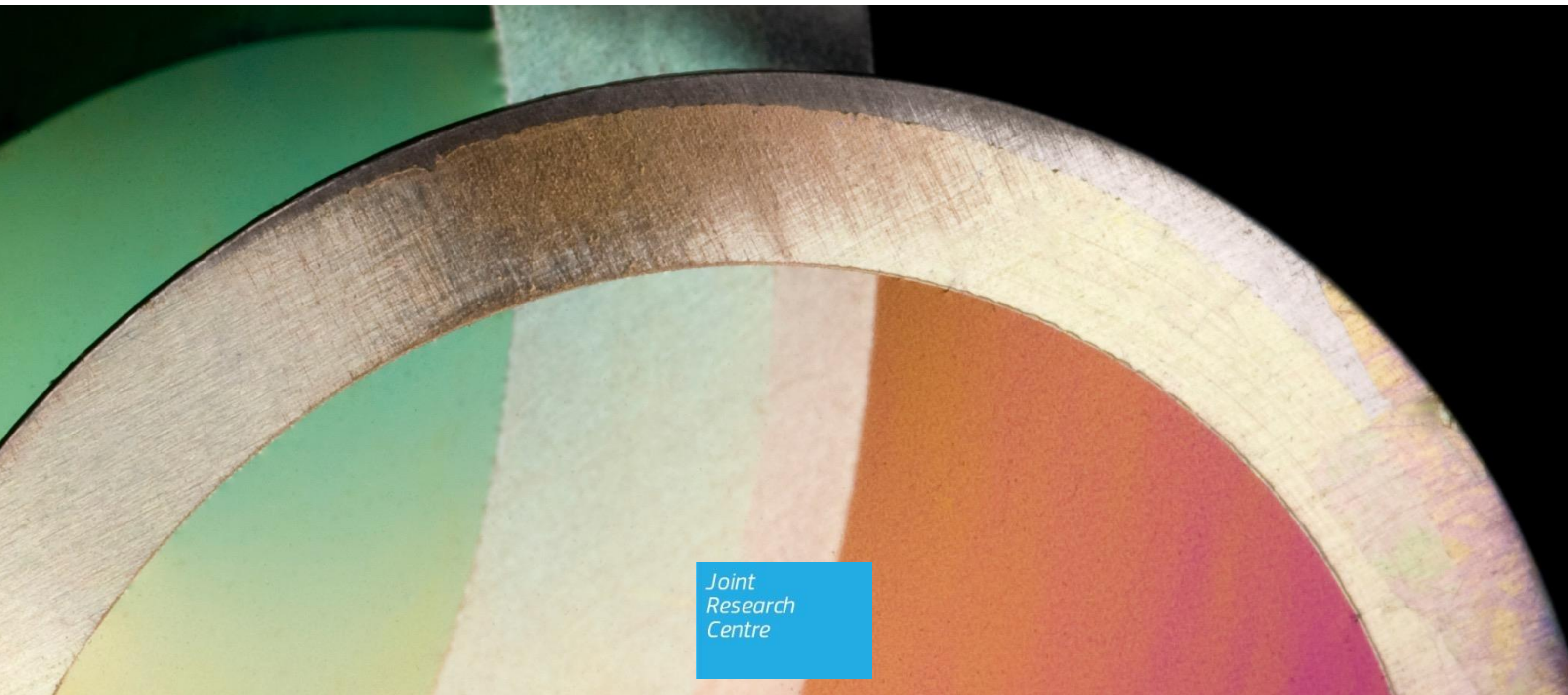

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Abstract

This study focuses on collaborative economy platforms that specialize in purely digital tasks that require no physical delivery or proximity between workers and their clients, which we call Online Labour Markets (OLMs). They have a global reach. There is a debate on job fragmentation and deteriorating working conditions in OLMs. This study emphasizes the economic opportunities and explores (a) the drivers of global trade in digital tasks, (b) the determinants of online wages and (c) the welfare impact of OLMs on workers and employers. This is a case study based on data obtained from a single UK-based OLM. Our findings cannot necessarily be generalised to other OLMs with different characteristics. Using panel data we find that the vast majority of employers are located in high-income countries while many workers are located in low-income countries. Workers in low-income countries are motivated to participate mostly by labour productivity gains and the corresponding higher wages. Workers in high income countries combine opportunities for additional work and income with the benefits of flexible time use and other non-wage benefits. Employers are motivated by wage savings and task unbundling. Despite the global nature of digital OLMs, there is an impression of home bias in hiring. OLMs are heterogeneous markets where about half of all transactions are settled above the lowest price bid. Workers' skills and experience as well as their countries of residence have an impact on the agreed wage and the probability of being hired. Worker quality signaling induces superstar effects and a very uneven distribution of work. Taking into account only the difference between online and offline wages in the countries of residence of workers and employers we estimate that this particular OLM has positive monetized welfare effects, both for workers (+17%) and even more so for employers (+70%). Unobservable non-monetized benefits such as increased flexibility and savings in transport or migration costs for workers and task unbundling for employers give a further boost to welfare. The extent of unbundling is demonstrated by the very short duration of the average task in this OLM: slightly less than 8 hours. Workers in this case study platform are self-employed and responsible for compliance with regulations in their country of residence.

Keywords: online labour market, sharing economy, gig economy, trade in digital tasks

JEL Codes: D40; J40

1. INTRODUCTION

The "gig economy" is a rather pejorative label that has been put on collaborative economy platforms or online "labour markets characterised by the prevalence of short-term contracts or freelance work as opposed to permanent jobs"[1]. This prejudice against collaborative economy platforms stems from their perceived negative welfare effects. Workers in these platforms are motivated by the revenue that they derive from this activity but have to contend with non-standard working conditions that are not as good as offline employment contracts. They lack social security coverage, there is a constant churn of highly fragmented very short-term tasks and they face uncertain employment prospects. In short, working conditions are far removed from the standard employee contract with pension rights, medical insurance, paid holidays, unemployment insurance, etc. - the gold standard for social welfare policies in modern societies. Workers have to assess whether the additional economic opportunities are worth the poorer working conditions and paying for their own social security.

Some argue that workers should not be confronted with this choice (Codagnone et al., 2016). Platforms should provide access to social security arrangements on top of the wages. Platforms are sometimes perceived as disguised forms of employment that help workers and employers avoid legal requirements for short-term contracts. Platform operators on the other hand often state in their Terms and Conditions that they are only intermediaries between workers and employers, and that users are responsible for complying with the law in their countries of residence, including taxes and social security contributions. Some well-known collaborative economy platforms are involved in high-profile court cases about the applicable labour market legislation. For example Uber, a well-known ride sharing service, faces court cases about the legal status of its drivers in several countries[2]. Typically, ride sharing and many other physical delivery services platforms require proximity between workers and their clients. That limits the geographical reach of these platforms to workers in local markets and makes the applicable regulation more obvious as well as the jurisdiction where claims can be contested.

Purely digital Online Labour Markets (OLMs) on the other hand require no physical proximity between workers and clients: they only deliver digital tasks. OLMs constitute global labour markets that offer opportunities for virtual migration: any worker anywhere in the world can deliver a digital service to any client anywhere in the world. Workers from low- and high-income countries compete for jobs in these markets. Well-known examples include digital task outsourcing platforms such as Amazon Mechanical Turk (AMT) and Upwork. Workers and employers are scattered across many jurisdictions. The applicable labour and social security legislation is not immediately obvious, let alone the competent court where claims could be submitted. Nevertheless, there have been calls for regulators to intervene and enforce adapted forms of labour conditions and social security legislation in OLMs (Berg, 2016; Codagnone et al., 2016).

This paper presents a case study of Peopleperhour.com[3] (PPH henceforth), a global OLM that delivers purely digital services that require no physical proximity between workers and employers. Using data from a UK-based OLM we present empirical evidence on the trade, competition and welfare effects for this case study. To the best of our knowledge, there are as yet no empirical estimates of the welfare benefits of OLMs for workers and employers. Our objective is to contribute to a balanced picture of OLMs where the gains from participation and the costs of less favourable working conditions can be compared.

[1] https://en.oxforddictionaries.com/definition/gig_economy

[2] See for example https://www.theguardian.com/technology/2016/oct/28/uber-uk-tribunal-self-employed-status

[3] We thank Peopleperhour.com for providing us with the necessary data to carry out this research, as well as for their invaluable help in understanding the functioning of the platform

In this case study we find that the vast majority of employers are located in high-income countries while many workers are located in low-income countries. Workers in low-income countries are motivated to participate mostly by labour productivity gains and the corresponding higher wages. Workers in high income countries combine opportunities for additional work and income with the benefits of flexible time use and other non-wage benefits. Employers are motivated by wage savings and task unbundling. Despite the global nature of digital OLMs, there is an impression of home bias in hiring. However most of that bias disappears when the relative availability of worker skills in countries is taken into account. OLMs are heterogeneous markets where about half of all transactions are settled above the lowest price bid. Workers' skills and experience as well as their countries of residence have an impact on the agreed wage and the probability of being hired. Worker quality signalling induces superstar effects and a very uneven distribution of work. We distinguish between monetised benefits generated by wage payments and non-monetised benefits that are not covered by wage payments. Based on the difference between online and offline wages in the countries of residence of workers and employers we estimate that this particular OLM has positive monetized welfare effects, both for workers (+17%) and even more so for employers (+70%). Welfare benefits may be substantially higher if we add non-monetized and only indirectly observed benefits from increased flexibility and savings in transport or migration costs for workers and task unbundling for employers. The extent of unbundling is demonstrated by the working time required for the average task in this OLM: slightly less than 8 hours. Workers are self-employed and should comply with the relevant regulations in their country of residence. It is challenging for national authorities to enforce local regulations in a global OLM with very low entry & exit costs.

This paper is structured as follows. Section 2 presents a short overview of the economic research literature on OLMs. Section 3 presents some descriptive statistics on the OLM case study, a UK-based OLM. Section 4 explores the international trade-in-tasks or virtual migration dimension of this type of OLMs and examines the drivers and impediments to global trade in task. Section 5 addresses price (wage) competition and heterogeneity in OLMs, the drivers of the observed wage patterns and substitution effects. Section 6 estimates the welfare effect on workers and employers[4]. It compares the online and offline wage distribution across countries to estimate the labour productivity gains from virtual migration. Section 7 concludes.

2. LITERATURE REVIEW

OLMs are an online extension of traditional domestic offline labour markets. Traditionally, firms recruit in local labour markets. However, firms looking for a more diverse set of skills will need a wider geographical reach in their search efforts. This is where intermediaries come into play in order to reduce search costs. Two-sided labour markets such as employment exchanges, interim agencies and government-sponsored employment agencies can facilitate more complex searches because they bring together many workers with a variety of skills and many firms looking for a variety of workers. Network effects and economies of scale reduce matching costs in this two-sided labour market platform set-up. They may evolve towards multi-sided markets when specialised intermediaries join the market such as in- and out-placement services, head hunters, social security and legal service providers etc. With the rise of the internet, most incumbent offline labour market intermediaries have at least partially moved their services online to reduce information costs. OLMs are a next step in that

[4] The use of the term "employer" in this paper should be interpreted in the economic sense of the demand side for labour, the party that seeks to buy labour services, as opposed to "workers" or the party that supplies labour services. It should not be interpreted in the sense of legal obligations with regard to labour market regulation and employment contracts.

evolution: they put the entire labour market process online, from search & matching between workers and employers to the delivery of workers' tasks, their output and wage payment.

There are many reports that aim to measure the rapid growth, the relative importance and the type of work and market organisation in OLMs. For example, Kässi and Ledhonvirta (2016) construct an Online Labour Index (OLI)[5] that provides an OLM equivalent of conventional labour market statistics. It measures the use of OLMs across countries and occupations in real time by tracking all the tasks posted on the five largest English-language online labour platforms[6], representing at least 60% of the market by traffic. They find that the market is dominated by jobs in software development and technology; only a small part of the vacancies are in professional services. OLMs are usually divided into low-skill (micro-tasks such as AMT) and high skill platforms. In this paper we focus on the second group.

The more analytical economic literature on OLMs starts in the late 1990s when online tasks were only a hypothesis. Malone and Laubacher (1998, 2003) predicted the upsurge of "*electronically connected freelancers—e-lancers*" that would completely change the industrial organization. Autor (2001) described three main changes that would take place due to the Internet: better matching between employers and employees; jobs done without the necessity of physical proximity and the impact on offline labour markets. Two decades later, online freelance work has become a reality.

Agrawal et al (2013) identify three main economic research questions regarding OLMs: the impact on the geographical distribution of work and on income distribution, the impact on welfare of workers and employers, and remaining information frictions in markets. Horton and Zeckhauser (2010) present a theoretical analysis of price structures in OLMs. They emphasize cost savings in telecommuting and more specialization in human capital. The geographical reach (and consequently the extent of specialization) of physical labour markets is limited by transport costs and (domestic and cross-border) migration costs for workers. Strict regulation of foreign migration in most countries, combined with linguistic and cultural barriers to migration, effectively reduces most labour markets to domestic markets only. Most online extensions of offline labour markets suffer from these limitations. Since the extent of specialisation is limited by the size of the market (Adam Smith, 1776), expanding the geographical reach via digitization should enable employers to "unbundle" tasks into small packages that require very specialized skills (Horton and Zeckhauser, 2010) and thereby increase productivity and wages for highly specialized workers.

Cullen and Farronato (2016) explore the growth, efficiency and benefits of peer-to-peer internet platforms using data from TaskRabbit. They find that a high elasticity of labour supply substantially contributes to the matching efficiency and growth of this multi-sided market. Exploring possible indirect network effects of the platform, they do not find evidence of economies of scale in matching. When both the number of offers and requests for tasks are doubled the number of successful matches increases proportionally. Cullen and Farronato (2016) conclude that platforms may rather focus on attracting buyers than on attracting sellers in order to promote their long-term growth.

Horton et al. (2017) explore the globalization process in online labour markets using a dataset from Upwork, the leader platform in OLM. They first explore how online labour markets deal with traditional offline barriers. Then, they tackle micro and macro-level questions. They find that distance still matters in the distribution of outsourcing contracts, although its impact is declining over time. One of their most striking findings is the very limited degree of self-provision of services by the countries in the sample (except US), despite the mentioned impact of distance. They also explore substitution patterns across countries. Their results suggest limited substitution of jobs between the

[5] http://ilabour.oii.ox.ac.uk/online-labour-index/
[6] Freelancer.com, Guru.com, Mturk.com, Peopleperhour.com, Upwork.com

United States and other countries, which point towards the existence of frictions. Finally, they pose new questions for future research.

Information costs to match supply (workers) and demand (employers) in labour markets are usually fixed costs, unrelated to the number of tasks or duration of the job. In order to amortize these fixed costs employers will tend to "bundle" tasks until they have a sufficient volume of work to justify the recruitment of an additional worker. In the traditional offline labour market these bundles of tasks come in standard packages of 40 hours per week. Some tasks are too small and infrequent to justify this package size. OLMs make it possible to fill this gap in the labour market. They reduce the fixed cost of recruitment and enable employers to search for workers for small tasks. That illustrates the impact of digital intermediation but also raise concerns about the "gig" economy: the fragmentation of work, the lack of social security and job security, etc.

While traditional markets rely on repeated personal interaction to create trust (Cabral and Hortaçsu, 2010) online markets without physical interactions require other mechanisms such as review scores. Straub et al (2015) use Amazon Mechanical Turk to test the efficiency of rank-order tournaments versus piece rates in term of incentives to crowd workers. Their results show the effects of feedback on worker's performance. Pallais (2014) demonstrates the crucial importance of a first job reference in order for workers to get started in an OLM. These first references are public goods that signal the quality of workers to potential employers. There is a sub-optimal level of hiring workers that have not been employed previously because first employers pay the costs (the risk of hiring a low quality worker) but do not reap the benefits of the externalities that a first reference generates. A good evaluation system could be a proxy for regulation (Einav et al., 2016; Dellarocas, 2003). Still, these mechanisms are far from perfect. Noisy ratings and strategic manipulation may result in socially harmful outcomes (Dellarocas, 2003). Unambiguous identification of OLM users is critical. If participants can change their identity at no cost, bad reputations can easily be masked in a new profile (Bolton et al., 2004).

Digital OLMs raise many social policy questions including the absence of social security provisions, long working hours and social isolation, downward pressure on pay and anxiety about finding new assignments and geographical discrimination. Horton et al. (2011) investigate complaints about "digital sweatshops" and the honesty of online employers who allegedly often refuse to pay workers or recruit them to produce spam and bogus reviews. They find no statistically significant difference in workers' trust of offline and online employers. Graham et al. (2017) highlight the risks and rewards for OLM workers in developing countries. Berg (2016) investigates poor working conditions in OLMs. The high variability of OLM tasks and the situation of workers make it hard to fit them in standard labour market regulation and social security that revolves around vertically integrated firms who hire workers as employees (Codagnone et al., 2016; Bock et al., 2016). OLM workers are independent and have no employee status, irrespective of where they live.

The debate on OLM's role as an employer or as intermediary is part of a wider debate on the status of online multi-sided markets or platforms that act as intermediaries between different types of users of the market (Martens, 2016). They are often accused of circumventing many types of regulations that were designed for the offline economy, not only labour market and social security legislation[7]. The role of OLMs is closer to that of an employment exchange or job search agency that puts workers and employers in contact with each other and leaves it to the two parties to agree on the terms and conditions for a contract. They remain intermediaries and are not employers in their own right. That makes them different from temporary work agencies that hire workers, set the wage rate and assume responsibility for an employment contract and social security contributions. Still, payments and

[7] The EU Posted Workers Directive (96/71/EC) does not apply here. A "posted worker" is an employee who is sent by his employer to carry out a service in another EU Member State on a temporary basis. OLM workers do not physically move to the country of the employer.

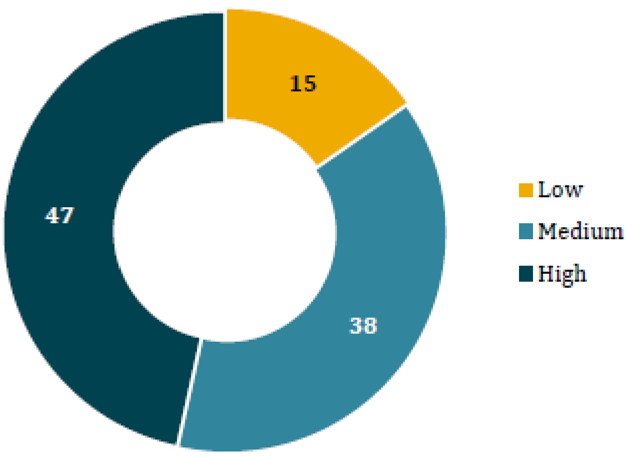
contracts pass through the OLM. They discourage direct contact between employers and workers to avoid by-passing of the platform fees once workers and employers have established a relationship. These makes OLM behaviour look more like temporary work agencies. In terms of duration of the task however our case study OLM clearly addresses a labour market segment for shorter-term jobs than the average temp agency: the average duration is slightly below 8 hours or one working day. Few employers would bother to go to a temp agency for such small tasks. Administrative and search costs would exceed the value of the work to be done. The strength of digital OLMs resides in their very low transaction costs and that pushes them towards new labour market segments that were left untouched by traditional offline labour market institutions and regulatory frameworks. If OLM would have to assume the responsibilities of temporary work agencies it would be very challenging to apply the wide variety of regulatory conditions applicable in the countries of residence of workers and employers in a single global OLM. Which country's rules would apply: the country of residence of the worker, the employer or the platform?

Berg (2016) uses an ILO survey of workers' motivations and frustrations in two OLMs, Amazon Mechanical Turk (AMT) and Crowdflower. Workers appreciate OLM work to complement income from other sources and/or because they have a preference for home work that offers more flexibility in organising their time: 40% consider online as their main job, 35% see it as complement to another job. US workers complain about low pay on AMT: 4.65 USD/hour on average for US workers while 7.25 USD is the minimum wage in the US. Compare this to 1.64 USD/hour for Indian workers while 0.22 USD/h is the minimum wage in India. Geographical market segmentation, enforced through geo-blocking on AMT, contributes to wage discrepancies. About 10% of workers report high wages over 10 USD/h on AMT. Clearly, higher wages are possible for some tasks & skills. Most workers would want to work more online. Berg (2016) claims that workers would not want to work if online wages were higher. This seems unlikely because it would imply a negative price elasticity of labour supply curve. This explanation conflicts with Horton and Zeckhauser's (2010) who find that labour supply in OLM increases when wages increase. Similarly, Gomez-Herrera and Mueller-Langer (2017) find an upward-sloping supply curve.

The ILO survey shows that despite digitization market entry and transaction costs can still be relatively high and much can still be done to improve the efficiency of online markets. Workers need to constantly monitor the website to find a job as competition is fierce. This can reportedly take 20% or more of working time. This reduces time flexibility. Monitoring costs are deadweight losses that increase with task fragmentation and reduce labour productivity and real wages. The survey responses point to high communication costs between workers and employers that may lead to high rejection rates in AMT. This reduces market efficiency, especially in auction-based OLMs that make it difficult to retain workers. Similarly, there are considerable costs for employers, having to post tasks repeatedly for verification and monitoring purposes and facing difficulties in retaining high quality workers, especially when direct contacts between workers and employers are difficult in some platforms. Pricing strategies have been explored to retain workers (Difallah et al. 2014; Gadiraju et al., 2015) but they may not be feasible in OLMs that rely exclusively on auctions and block direct contacts. Some OLMs experiment with direct contacts between workers and employers. Upwork for example enables employers to integrate workers into their internal computing systems and monitor performance in real time.

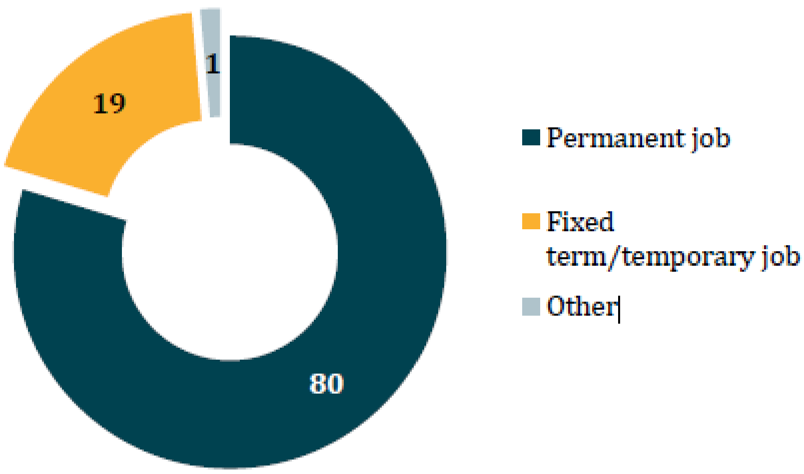
The JRC Digital Labour Markets survey (forthcoming) was conducted a survey of OLM in 14 EU countries. The findings emphasize the importance of non-monetary welfare gains for workers. The main motives to engage in digital labour are (a) flexibility over place (71% very or fairly important) and time (69%) of work, (b) compatibility with family commitments (59%), (c) interesting and fulfilling work (59%) and (d) being one’s own boss (59%). As Figure 1 shows, online workers are skilled and employed in the offline economy: 85% have a medium or high level of education. Additionally, 76% of respondents report having an offline job, either as an employee or self-employed. Figure 2 shows that, out of the people that reported to have an offline job, 80% declare it to be a permanent job. These findings point toward complementarity rather than substitution between online and offline jobs, at least in the EU. Workers benefit from the fact that OLMs enable employers to "unbundle" tasks while offline jobs usually come in fixed amounts of "bundled" time, the standard 40 hours working week. Institutional constraints in the labour market and organisational constraints at firm level imply that they cannot easily be stretched into overtime and more hours, even if workers would like to do so. Taking up short "unbundled" online tasks provides the flexibility to work more hours.

Figure 1. Education level of online workers



Source: JRC Digital Labour Markets survey in the EU (forthcoming)

Figure 2. Offline employment situation of online workers



Source: JRC Digital Labour Markets survey in the EU (forthcoming)

Note: This figure represents 76% of the respondents who reported to have some offline job. The remaining 24% do not have any offline job.

3. SOME DESCRIPTIVE STATISTICS

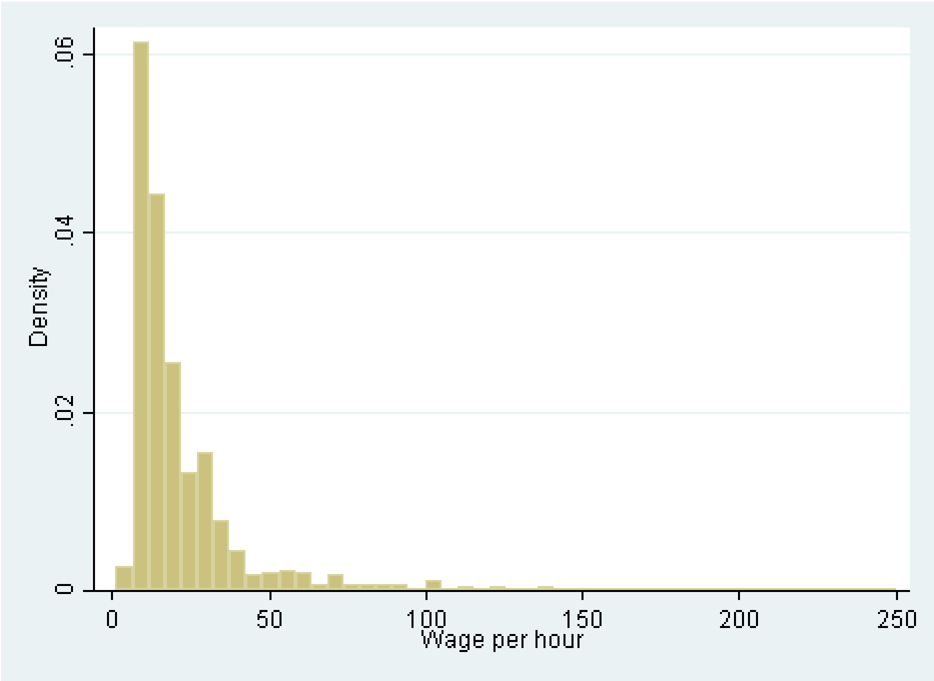
We use data from a UK-based OLM platform, People-per-Hour (PPH), founded in 2007 in London. It is one of the largest EU-based OLM for digital tasks. By end-2016 it had about 122,000 registered workers (freelancers) and 90,000 employers (clients) and an annual turnover around 10 million Euro. Still, PPH is much smaller than Upwork, the US-based OLM world market leader with more than 650,000 registered workers and over 1 billion USD in annual turnover.

Like all multi-sided markets OLMs subsidize one side of the market and charge the other side (Parker and Van Alstyne, 2005) in order to maximize revenue and leverage network effects. Employers have free access to the platform and pay no fees. The platform currently charges workers a 20% fee on their earning up to 520 €/month and 5% thereafter. This digressive fee schedule, combined with the importance of building up a track record of successfully completed tasks, gives an incentive to highly rated workers to stick to the platform and avoid multi-homing between several OLM platforms. Workers without ratings or with low ratings have an incentive to multi-home between OLMs in order to find a platform where they can get started with a good rating. Employers can easily multi-home without additional costs. The difference in multi-homing incentives between workers and employers explains the fee structure in the platform.

Our dataset covers all transactions from Nov 2014 to Oct 2016. It comprises 132,759 completed tasks involving 59,569 employers from 179 countries and 21,685 workers from 181 countries. 121,733 tasks were agreed on the basis of a fixed budget or wage bill[8]. The total wage bill for these projects reached nearly 20 M€, an average of 164€ per task. The remaining 11,026 tasks were settled on the basis of an agreed hourly wage rate. Our data set thus comprises two types of tasks, one for which we observe only the agreed wage bill and a second for which we observe only agreed hourly wages[9]. We decompose wage bill tasks into price (wages) and quantity (time). For this purpose we identified workers who carried out both hourly wage rate and wage bill tasks. This is the case for 57% or 69,511 out of 121,733 wage bill tasks. We divide the value of the wage bills by these workers' observed hourly wage rates to estimate time spent on these wage bill projects. Figure 3 shows the wage distribution across tasks. Some tasks reach exceptionally high wage rates[10] but the bulk is situated in the 5-50€/hour interval. The median wage is 20.82€, the average 33.09€. We repeat the analysis for the top 5% workers and the top 5% and find no significant differences in the distribution[11].

[8] Wage bills are the product of wage and working time (price times quantity).
[9] Besides these two types a third type of "hourlies" tasks exists on PPH. They account for 197,960 out of the 346,895 tasks awarded over the entire period. These are small tasks with a fixed price and no bidding process. We excluded these tasks from the data. We also excluded 16,176 tasks for which there was no information on workers.
[10] We capped hourly wages at 250€/hour, which covers 99% of all hourly wage tasks.
[11] Figures available upon request.

Figure 3 | Distribution of wage per hour



Note: For the sake of clarity, we exclude in the figure wages higher than 250€/hour, which are less than 5% of the sample. However, we do not make this restriction on the data used in our regressions.

Contrary to many other OLMs, PPH imposes a minimum wage rate of 7€ or 6£ or 10$ per hour. This comes close to but remains below the legal minimum wage for adult workers in the UK[12] that stood at £6.70 from 1 Oct 2015 and was raised to £7.20 in 2016. However, only 48 tasks (0.4%) posted by UK employers and 36 tasks (0.3%) completed by UK workers had an agreed hourly wage below the legal minimum in the UK[13]. Table 1 reports minimum wage rates in the top-10 major worker and employer countries and shows the number of tasks where the agreed wage was below local minimum wage rates in the country of the worker. Worldwide, only 3% (336 tasks) were below the platform minimum rate. 2.6% (288 tasks) of these were carried out by non-UK workers.

Table 1 illustrates the conundrum that global OLMs pose for minimum wage legislation. Even if OLMs wish to stick to the rules, whose rules should they apply? Should the rules of the country of residence of the employer, the worker or the platform apply? In this case study for example, should UK rules apply because it is legally based in the UK? The worker performs the tasks in his country of residence, not in the country of the employer. Since global OLM only emerged on a significant scale in the last couple of years there are no ILO standards or other regulations that determines which minimum wage regime should apply in these cases.

[12] See http://www.minimum-wage.co.uk/

[13] Some of these may be tasks that require less than 1 hour of work.

Table 1 | Number of projects below the minimum hourly wage, by country

Top 10 workers' countries	Minimum hourly wage (EUR, 2013)	Nr of projects agreed wage below minimum wage in worker country
India	0.22	1
United Kingdom	6.95	36
Pakistan	0.43	1
United States	5.48	4
Bangladesh	0.3	0
Spain	4.36	0
Ireland	8.46	0
Ukraine	0.66	0
Philippines	1.25	0
Romania	1.05	0

Top 10 employers' countries	Minimum hourly wage (EUR, 2013)	Nr of projects agreed wage below minimum wage in employer country
United Kingdom	6.95	48
United States	5.48	12
Australia	11.35	50
Canada	7.49	6
Germany	6.96	4
United Arab Emirates	NA	NA
Ireland	8.46	2
France	8.28	7
Spain	4.36	0
Netherlands	8.56	3

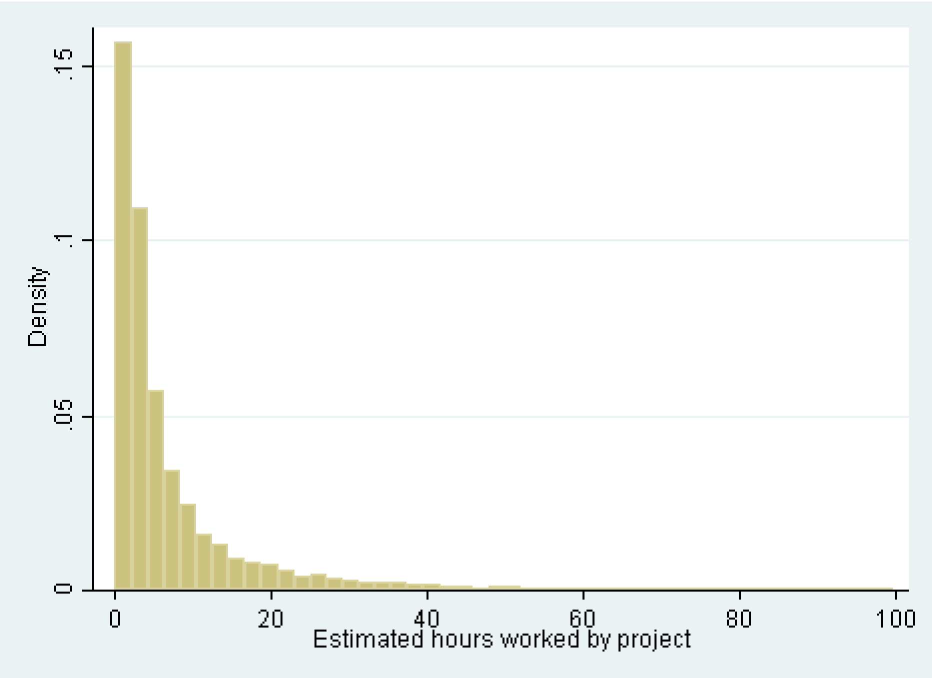
Source: ILO and data provided by PPH.

OLMs operate in a more fragmented market compared to traditional full-time and even part-time employment. Figure 4 shows the high degree of task unbundling as reflected in the distribution of working hours across tasks. Most tasks require only a few hours of work. The median duration of tasks is 3.5 hours; the average 7.9 hours[14]. This confirms the high degree of fragmentation in the platform, in line with reports on other platforms (Berg, 2016; Horton and Zeckhauser, 2010). Arguably, employers would not be able to outsource such small tasks through traditional offline labour markets. Market entry and selection costs would be too high. Organizing social security schemes in such a highly fragmented labour market would be challenging. Current administrative procedures in most countries would create prohibitively high market entry costs for very small tasks. Procedures would have to be digitized and simplified to match the very low level of transaction costs in OLMs. Moreover, this would require global agreements in order to prevent market displacement

[14] The distribution of working hours per task was capped at 100 hours.

effects. Again, we find no significant differences in the different distribution for superstar workers and employers[15].

Figure 4 | Distribution of estimated hours worked by project



Note: For the sake of clarity, we exclude in the figure tasks over 100 hours worked, which are less than 1% of the sample in terms of projects and 20% in terms of hours worked. However, we do not make this restriction on the data used in our regressions.

Table 2 shows the percentile distribution of the wage bill across workers and employers. The bottom 50% of workers account for barely 3% of the entire wage bill, while the top 1% accumulates 27% of the wage bill. The distribution is more equal among employers where the bottom 50% accounts for 21% of the wage bill and the top 1% for 5.5%. There is much more concentration of transactions among workers than among employers. This indicates that many workers have a hard time getting into the market.

Table 2 | Wage bill distribution for workers and employers

	Agreed wage bill	
Percentile	**Workers**	**Employers**
10.00%	0.10%	1.30%
25.00%	0.60%	5.90%
50.00%	3.20%	21.00%
75.00%	12.00%	48.20%
90.00%	29.90%	
99.00%	73.00%	94.50%

Source: Data provided by PPH.

[15] Figures available upon request.

The top-100 workers in the platform in terms of revenue (or total wage bill) do nearly twice as many (10) tasks per month, compared to 5.3 for the average worker, work on larger projects (24h compared to 9.8h on average) but earn slightly lower wages per hour (14.4€). Their quality rating is considerably higher (4.15) than the average worker (3.20). In short, their earnings are driven by working harder and bidding lower prices despite a higher rating. The top-100 employers do not post more tasks (5.25 /month) than the average employer (5.33 /month). However, they post tasks that are 6 times larger than the average task (wage bill of 962€ compared to 154€[16] on average; 62h work per task compared to 9.8h on average) that require slightly higher experience (2.15 instead of 2.00) and pay slightly less per hour (15€). In other words, the top employers post bigger projects.

The highly unequal distribution on the worker side of the platform suggests superstar effects (Rosen, 1983). Workers with a good track record may attract more work and thereby boost their track record. The direction of causality is often hard to determine however (Moraga-Gonzalez et al., 2013). Agarwal et al. (2013) pointed out the public good nature of review scores given by employers. Pallais (2014) demonstrated the high marginal rate of return of receiving a first review score, even if the information content was very limited. The concentration of tasks in the hands of a relatively small group of top-ranked workers may not only be the result of reduced information costs but also due to narrowing of workers' signalling bandwidth to a few variables, compared to offline labour markets where CVs and interviews provide a more costly but also a wider communication channel between workers and prospective employers. Berg (2016) notes that workers frequently complain about narrow communication channels that reduce the efficiency of work.

In PPH, tasks are classified in 17 categories. Arguably, the types of skills required may vary across these categories. Table 3 reports the number of tasks and the wage bill (revenue) generated by each category, as well as the average wage bill per category. Design, web development and writing are the largest categories. The average wage bill shows that mobile phone, software and web design and system analytics tasks are the most expensive ones. At the bottom end are writing, translation, social media and administrative tasks. Admin, software design and translation require less skilled workers while system design, social media and marketing tasks attract the highest rated workers. The type of tasks has an impact on remuneration (see section 5).

[16] The top-100 calculations are based on a sub-sample of 57% of all wage bill projects for which we also have information on wages per hour for the workers. As a result, the average wage bill is only 154€/hour and not 164€/hour, the average for the entire sample.

Table 3 | Summary statistics by job category

Category	Number of job openings	Number of contracts	Number of cross-border contracts	Cross-border contract share	Wage bill, (EUR thousands)	Wage bill from cross-border contracts	Cross-border wage bill share
Unknown	172,205	27,256	15,478	56.80%	4,536.70	2,566.30	56.60%
Design	88,156	37,309	22,436	60.10%	3,593.90	1,958.90	54.50%
Web Development	71,761	25,968	17,877	68.80%	4,844.20	2,965.70	61.20%
Writing	31,709	13,075	5,747	44.00%	1,170.20	465	39.70%
Business Support	26,990	7,423	3,442	46.40%	907.3	379.3	41.80%
Video, Photo & Audio	26,012	8,800	5,526	62.80%	1,017.90	522.5	51.30%
Marketing & PR	21,695	4,123	1,912	46.40%	463.5	180	38.80%
Admin	18,715	6,252	3,345	53.50%	352.7	188.8	53.50%
Software Dev	18,083	4,122	3,115	75.60%	1,204.40	862.6	71.60%
Social Media	10,526	2,192	1,230	56.10%	178.7	86.1	48.20%
Search Marketing	10,356	2,371	1,387	58.50%	318.2	151	47.50%
Translation	10,174	4,493	3,666	81.60%	367.5	292.2	79.50%
Mobile	8,278	1,404	1,165	83.00%	854.7	725.2	84.80%
Creative Arts	5,323	1,433	870	60.70%	139.5	84.4	60.50%
System	2,593	2,050	1,215	59.30%	345.6	222.4	64.40%
Tutorials	2,411	405	274	67.70%	37.2	22.5	60.40%
Extraordinary	2,145	259	140	54.10%	35.3	18.8	53.20%
Total	527,132	148,935	88,825	59.60%	20,367.50	11,691.60	57.40%

Source: Data provided by PPH.

Table 4 | Hiring and working patterns for top countries on the platform (ranked by wage bill)

Country	Employer wage-bill rank from cross-border contracts	Worker wage-bill rank from cross-border contracts	Nr of cross-border hiring contracts	Nr of cross-border worker supply contracts	Wage bill from cross-border hiring, (EUR thousands)	Wage-bill from cross-border supply, (EUR thousands)
United Kingdom	1	2	45,022	12,285	5,917.20	1,876.30
United States	2	4	13,386	5,025	1,879.70	652.4
Australia	3	23	2,471	453	310.8	62.8
Canada	4	12	1,838	812	263.4	127.6
Germany	5	13	1,426	876	214.6	125.3
UAE	6	15	1,079	553	192.4	105.1
Ireland	7	7	1,687	976	182.2	201.5
France	8	16	1,089	877	164.6	92.6
Spain	9	6	1,177	1,524	145	206.4
Netherlands	10	17	1,133	630	141.9	89.9
Saudi Arabia	11	94	749	36	140.3	2.7
Singapore	12	44	747	316	139.7	31.8
Nigeria	13	28	569	504	134	52.3
Switzerland	14	39	779	266	132.7	34.8
India	15	1	1,377	25,731	131.4	4,458.20
Malaysia	16	40	456	281	120.1	33.6
Belgium	17	59	645	142	109.4	16.3
Italy	18	65	746	1,144	106.4	119.4
Greece	19	11	555	1,420	76.3	130.3
South Africa	20	31	459	486	75.5	50.3

Source: Data provided by PPH

4. INTERNATIONAL TRADE IN TASKS IN OLMS

Trade-in-task is a well-known concept in the international trade literature (Grossman and Rossi-Hansberg, 2008; Baldwin and Nicoud, 2014). Workers stay in their home country and embody their skills in locally produced physical goods that are shipped to the destination country. Digital OLMs give new meaning to the concept of trade-in-tasks. Skills are not embodied in physical goods but in digital services. The difference is that goods still face trade costs (physical transport costs) while digital data files have zero transport costs. However, digital trade does not completely eliminate trade costs. Research on online cross-border trade (Blum and Goldfarb, 2006; Gomez-Herrera et al, 2014) has demonstrated that the "death of distance" hypothesis is exaggerated. Some sources of trade costs persist such as language, time zones and cultural distance. Trade-in-tasks embodied in goods is often seen as an economic alternative to migration from developing to developed countries. This argument may be even stronger for trade-in-tasks embodied in digital services. Workers avoid the high costs of physical migration while they can still benefit from higher labour productivity and wages in developed countries by bidding online for tasks in high wage countries. Workers in trade-in-tasks embodied in goods usually get very little wage premium above prevailing wages in their home country. We will address these questions below.

Table 3 gives a first impression of the extent of cross-border trade in tasks in the platform. Almost 60% of all tasks are outsourced internationally. Mobile, software & web development and translation tasks are most frequently traded across borders. At the other end of the spectrum, writing, business support, admin and marketing & PR are least frequently traded, presumably because they require more local cultural connection. Table 4 shows the ranking of countries according to their cross-border flows. United Kingdom is the country that hires more volume from abroad, whereas India is the one that works more for foreign countries.

Tables 5A and 5B present a bilateral trade matrix for task trade flows in the platform at the extensive margin (number of tasks) and the intensive margin (wage bills)[17] for the top-10 worker and employer countries. Other countries are aggregated in the "rest of the world" category. In line with Kässi and Lehdonvirta (2016), our trade matrix shows that employers are mostly located in higher-income countries while workers are mostly located in lower-income countries. This suggests that labour productivity and wage gains for workers in low income countries and wage savings for employers in high income countries are important (but not necessarily the only) drivers for OLM work.

[17] For the extensive margin trade matrix we take all observed tasks in the platform. For the intensive margin trade matrix we only take wage bill tasks. We have no quantity of time for the hourly wage rate projects.

Table 5A | Bilateral trade flows in the OLM platform (extensive margin, number of tasks)

Workers / Employers	GB	EU	US	CA	AU	IN	PK	BD	PH	UA	row	Total employers	%
GB	51,117	3,846	2,796	427	265	13,399	4,253	2,943	791	735	10,824	91,396	68%
EU	2,096	612	275	33	22	1,390	302	279	77	115	1,114	6,315	5%
US	3,333	518	1,697	124	40	3,104	983	820	205	227	2,523	13,574	10%
AU	616	100	110	9	46	585	135	202	57	45	386	2,291	2%
CA	456	89	147	59	3	362	110	94	32	30	309	1,691	1%
IN	347	68	138	15	5	1,102	184	107	19	30	294	2,309	2%
PK	82	19	37	2	1	158	128	36	8	10	87	568	0%
BD	22	4	13	2		59	18	138	4	6	35	301	0%
PH	38	10	18	1		56	7	25	7	2	42	206	0%
UA	34	13	8	1		16	3	2		23	33	133	0%
row	4,082	863	878	104	56	3,825	1,044	716	218	266	3,449	15,501	12%
Total workers	62,223	6,142	6,117	777	438	24,056	7,167	5,362	1,418	1,489	19,096	134,285	100%
%	46%	5%	5%	1%	0%	18%	5%	4%	1%	1%	14%	100%	

Source: Data provided by PPH, authors' own calculations.

Table 5B | Bilateral trade flows in the OLM platform (intensive margin, value of trade)

Workers/ Employers	GB	EU	US	CA	AU	IN	PH	PK	BD	UA	row	Total	%
GB	7,955,656	549,421	378,340	78,471	37,721	2,299,408	73,078	442,955	174,225	86,937	1,254,699	13,330,912	69%
EU	287,953	76,232	47,768	5,071	3,616	208,461	9,122	25,747	17,875	14,150	127,581	823,578	4%
US	512,555	64,691	246,330	17,813	4,374	567,262	24,189	125,733	57,934	16,656	292,570	1,930,106	10%
CA	60,042	14,897	23,295	7,056	375	70,190	3,239	15,033	5,372	2,913	44,298	246,710	1%
AU	106,628	10,151	11,110	985	6,074	80,920	7,506	17,008	11,008	4,179	35,513	291,082	2%
IN	36,205	8,486	8,836	958	824	114,295	2,092	25,850	5,331	3,525	26,099	232,501	1%
PH	4,380	814	1,577	50		3,417	256	269	586	177	2,601	14,127	0%
PK	6,106	1,252	1,182	127	43	10,942	358	9,489	1,289	466	7,981	39,234	0%
BD	727	81	562	48		2,964	107	315	3,599	299	2,292	10,994	0%
UA	1,985	866	536	59		2,240		28	292	4,294	1,799	12,098	0%
row	692,542	141,049	114,155	13,903	8,527	783,390	29,441	137,203	47,279	37,484	407,627	2,412,601	13%
Total	9,664,780	791,707	833,692	124,539	61,553	4,143,489	149,389	799,631	324,789	171,080	2,203,059	19,267,709	100%
%	50%	4%	4%	1%	0%	22%	1%	4%	2%	1%	11%	100%	

Source: Data provided by PPH, authors' own calculations.

There is strong home market bias in the platform. It is based in the UK which is also its main market: 46% of all workers and 68% of all employers reside in the UK. 41% of the wage bill circulates between workers and employers in the UK only (increasing to 46% when we take an EU perspective). Since nearly 70% of all employers are located in the UK (and 89% in the EU and US), all other countries export the bulk of their virtual labour to the UK. UK workers only export 18% of their labour to other countries, the US 70% and the EU 91%. The propensity to export reaches close to 100% for lower income Asian countries. Conversely, UK employers seem to have a preference for UK workers and import only about 40% of their virtual workers, while EU and US employers import around 90%. Asian employers represent only a very small percentage of the total number of employers in the platform; however, they outsource a considerable part of their tasks to local workers, especially in India where local workers account for about 50% of tasks outsourced by Indian employers. Finally, the strong trade-in-task ties between the UK and India are apparent in this trade matrix: India accounts for 18% of all tasks and 21% of all workers. This might be due to strong ethnic ties in virtual outsourcing (Horton et al., 2017). The Indian community in the UK and elsewhere may prefer to outsource to India. It may also be related to India's comparative advantage in ICT services industries and the fact that a majority of tasks are ICT technology related.

We explore the drivers of cross-border trade in digital tasks in the platform more formally with the help of a gravity trade model. Gravity models estimate bilateral trade in function of the geographic, economic, cultural and other distance-related trade costs between country pairs. The gravity model has proven to be successful when predicting trade flows. Anderson (1979) and Bergstrand (1985) contributed to its theoretical foundation and substantial improvements were suggested by Baier and Bergstrand (2001) and Anderson and van Wincoop (2003). Following Santos-Silva and Tenreyro (2006), we use Poisson Pseudo Maximum Likelihood (PPML) for the estimation of the gravity equation. This estimator is robust to different patterns of heteroscedasticity and provides unbiased and consistent estimates. Besides it allows the inclusion of zero flows in the estimation since the dependent variable is specified in levels and not in logarithms[18].

Despite the absence of transport costs, geographical distance continues to have a negative impact on trade in virtual tasks. This illustrates once more that the "death of distance" hypothesis (Cairncross, 1997) in online markets was overoptimistic. While information costs are greatly reduced and physical transport costs may be eliminated for purely digital transactions, other distance-related trade costs such as language and cultural distance still play a role (Lendle et al., 2016; Gomez-Herrera et al., 2014; Blum and Goldfarb, 2006). Distance still matters in online transactions. Horton et al. (2017) apply gravity modelling to global OLM trade flows, using Upwork data and come to similar conclusions.

We estimate the following gravity equation, both at the extensive margin (number of tasks traded) and the intensive margin (value of tasks, or wage bill):

$$\begin{aligned} Wage\_bill_{od} = {} & \beta_0 \\ & + \beta_1 \log dist_{od} + \beta_2 \log past_{trade_{od}} + \beta_3 \log(GDP_o - GDP_d) \\ & + \beta_4 colony_{od} + \beta_5 same\_country_{od} + \mu_o + \mu_d + \varepsilon_{od} \end{aligned} \tag{1}$$

where *o* is the worker country of origin and *d* is the (destination) country where the employer is located. We use three explanatory variables that reflect the economic distance between country pairs: geographic distance

[18] Since the logarithm of zero is undefined, using logarithms for the dependent variable implies that an important part of the dataset is automatically discarded, thus creating a bias in the estimation

($dist_{od}$), past trade volume ($past\_trade_{od}$), differences in GDP per capita ($GDPpc_o$ – $GDPpc_d$). We add a dummy that takes value 1 when country pairs have been in a colonial relationships and another when worker and employer reside in the same country. The latter enables us to measure the extent of home bias or employers' inherent preference for workers from the same country. In line with the empirical findings from the offline trade literature, also confirmed for online trade (Lendle et al., 2016; Gomez-Herrera et al., 2014; Blum & Goldfarb, 2006), we expect a negative sign on the coefficient for distance and positive signs on all other coefficients including home bias, difference in GDP per capita, former colonial relationships and past offline trade volume. The dependent variable, i.e. number of tasks traded or the size of the wage bill is defined at the country pair level: two countries that actually have task trade flows in the data set. Out of all theoretically possible 179 x 181 = 32,399 country combinations[19], we find that only 2,125 country pairs actually have trade flows. We introduce worker and employer country fixed effects in the regression to control for country-specific factors that may affect trade, such as variations in average skill levels among countries or origin of workers.

The country-level gravity model regression results (Table 6) are in line with expectations. Despite digital trade, geographical distance continues to have a negative impact on trade. Past trade volumes and colonial ties have a positive effect on trade. We find no statistically significant impact on the value of trade (wage bill). The country-level analysis confirms the presence of home bias, even when we leave out the UK observations (last two columns in Table 6). We find that differences in GDP per capita between the employer and worker country have a negative impact on the number of tasks traded. This suggests that the wider the economic gap between worker and employer country, the harder it is for workers to enter the OLM. However, the economic gap may also coincide with a skills gap. We will show in section 6 below that this income effect disappears when we bring worker skills profiles into the analysis. Horton et al (2017) use Upwork data and find a positive impact of differences in GDP per capita on the wage bill.[20]

[19] The number of workers' countries and employers' countries observed in our dataset.
[20] Notably, they use dummy variables for categorized differences while we use a continuous variable for GDP per capita in our analysis.

Table 6 | Determinants of cross-border flows

			No UK-UK	No UK-UK
Dependent variable:	**Wage bill**	**Nr projects**	**Wage bill**	**Nr projects**
Log weighted distance (pop-wt, km)	-0.208***	-0.189***	-0.207***	-0.189***
	(0.064)	(0.028)	(0.063)	(0.028)
Log past trade volume, avg 2000-2013	0.045	0.054***	0.051	0.054***
	(0.034)	(0.014)	(0.033)	(0.013)
Log difference in GDP pc between	-0.042	-0.060***	-0.036	-0.060***
countries, in 1000	(0.044)	(0.022)	(0.043)	(0.022)
Pair ever in colonial relationship	0.164***	0.189***	0.191***	0.189***
	(0.050)	(0.036)	(0.059)	(0.042)
Employer and worker in same country	1.607**	1.800***	1.618**	1.801***
	(0.672)	(0.268)	(0.669)	(0.259)
Constant	-8.246***	-5.438***	-8.290***	-5.439***
	(0.627)	(0.263)	(0.613)	(0.256)
Employer country FE	Yes	Yes	Yes	Yes
Worker country FE	Yes	Yes	Yes	Yes
Observations	2,126	2,126	2,125	2,125

Note: We use a cross-section. Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. PPML estimation.

5. WAGES, SKILLS AND RATINGS COMPETITION IN OLMS

Our data show that only 50% of all agreed bids are equal to or lower than the lowest price bid. That begs the question what drives wages above the lowest bids received by employers? To what extent do variations in worker characteristics push OLMs away from pure price (wage) competition and create quality heterogeneity in markets?

The bidding data provide a detailed picture on the internal bargaining dynamics of the platform, including the role of individual skills and experience in this heterogeneous labour market. Bargaining starts when an employer posts a task with technical specifications and a proposed hourly wage or total wage bill. Workers submit bids and the employer accepts one bid. For all accepted tasks we observe the total wage bill or the hourly wage rate that an employer and a worker agreed upon after a bargaining process. As for the bargaining process, we observe the wage (bill) proposed by the employer at the start of the bidding process (if any), the number of bids received and the quality of the workers who made a bid, as proxied by their ratings from previous employers. We obtain individual worker characteristics such as the total number of completed tasks and expected wage as indicated on the worker's web profile. We observe the number and characteristics of previous tasks of an employer. Task characteristics include size (working time), experience required and category of the task. We add worker country characteristics (gross domestic product per capita).

In order to estimate the contribution of worker, employer and task characteristics to the agreed price of a task, as measured by the agreed hourly wage or agreed wage bill, we estimate the following regression:

$$\begin{aligned}\log price_{ijp} = \beta_0 &+ \beta_1 \log exp\_worker_i + \beta_2 avg\_rat_i + \beta_3 interactions_{ij} \\ &+ \beta_4 \log exp\_empl_j + \beta_5 \log nr\_bids\_adj_{ijp} + \beta_6 \log hours_{ijp} \\ &+ wage\_bill\_prop_{ip} + \mu_o + \mu_c + \mu_c + \varepsilon_{ijp}\end{aligned} \quad (2)$$

where *i* is the employer, *j* is the worker and *p* is the project. The explanatory variables can be grouped into worker, employer and task characteristics.

Worker characteristics include the number of previously completed tasks (exp_worker_i), the average rating of the worker for previous tasks (avg_rat_i), and the number of previous interactions with the same employer who posted the task ($interactions_{ij}$).

Employer characteristics include the proposed wage or budget ($wage\_bill\_prop_{ip}$), the experience level required by the employer (exp_emp_j) and the number of tasks posted previously by the employer.

Task characteristics include the number of bids received adjusted by the rating of the worker that makes the bid ($nr\_bids\_adj_{ijp}$), task size -hours of working time –($hours_{ijp}$) and the category of the task. μ_o, μ_d and μ_c are fixed effect dummies for workers' countries of residence (origin), employers' countries of residence (destination) and task categories. The reference country is the UK in both sets of country dummies and the reference category is 'Administrative'.

We run this regression with two dependent variables: agreed hourly wages and agreed wage bills (i.e. wages times working time). In the latter case we control for task size or working time. We have 11k observations for the first regression and more than 120k for the second. The results are presented in Table 7.

The first two columns of Table 7 show results for the hourly wage regression. Clearly, worker quality matters in the determination of wage rates and introduces heterogeneity in the OLM: more experienced workers (more previous projects) with better ratings and more previous interactions with the same employers obtain higher wages. Building up a good track record is important for workers in a relatively anonymous OLM. Employers who require more experienced workers drive up wages. In fact, experience required is the most important driver of the hourly wage rate. More experienced employers who have posted tasks before tend to get a better deal and pay lower wages compared to novice employers. Somewhat surprisingly, an increase in the number of bids made for a task increase the hourly wage rate. One would expect that more competition drives down the agreed wage but that does not seem to be the case here. Arguably, this counterintuitive result may be due to the fact that it is not possible to control for task size in the agreed hourly wage sample. We address this issue in the following. The two last columns in Table 7 use a much larger sample of 122k wage bill observations and control for task size (number of hours required). Obviously, the latter variable has a major effect on wage bills. After controlling for task size, results are mostly similar to the hourly wage regressions, except for employers who propose a price. Employers who propose an hourly wage when they post a task end up paying less. However, employers who propose a wage bill tend to pay more than those who don't. A notable difference between the results for the wage sample and the wage bill sample is the effect of competition. Controlling for task size, we find evidence that more competition is associated with lower agreed wage bills in the last two columns of Table 7.

Category fixed effects (Table 8) are ranked from highest to the lowest wage premium according to the last column (wage bills). The reference category is administrative work, the lowest paid task category. System design, search marketing and software development tasks fetch strong premium prices compared to administrative work. At the other end of the scale, hourly wages for translation, writing and social media work do not seem to fetch much premium over the lowest paid administrative work category.

Country fixed effects for these regressions are also shown in Table 8 for a selected sample of EU and a few other countries. Country effects are ranked from weakest to strongest according to the last column (wage bills). In general, the hourly wage regressions have few statistically significant country fixed effects, neither for employer nor for worker countries. The wage bill regressions show considerably more significant country effects, also because sample size is much larger (122k compared to 11k observations, for 180 countries). It is hard however to discern any meaningful patterns in these country fixed effects.

Table 7 | Drivers of agreed wages and wage bills in OLMs

Dependent variable	Log hourly wage	Log hourly wage	Log wage bill	Log wage bill
Log cumulative number of projects completed by the worker up to that date	0.048**	0.042**	0.030***	0.026**
	(0.017)	(0.015)	(0.01)	(0.01)
Average employers' rating of worker	0.017***	0.015**	0.022***	0.021***
	(0.006)	(0.005)	(0.002)	(0.002)
Log number of interactions between employer and worker	0.061**	0.054**	0.063***	0.059***
	(0.023)	(0.021)	(0.013)	(0.012)
Experience level required for the project		0.393***		0.229***
		(0.016)		(0.016)
Log quality-adjusted number of bids	0.124***	0.111***	-0.041***	-0.046***
	(0.025)	(0.022)	(0.009)	(0.009)
Employers propose budget or hourly wage	-0.149***	-0.083***	0.169***	0.162***
	(0.022)	(0.017)	(0.028)	(0.023)
Log cumulative number of projects posted by the employer up to that date	-0.062***	-0.076***	-0.058***	-0.065***
	(0.016)	(0.016)	(0.007)	(0.009)
Log approximate number of hours required for the job			0.853***	0.819***
			(0.017)	(0.024)
Constant	2.644***	2.014***	2.758***	2.435***
	(0.044)	(0.034)	(0.048)	(0.047)
Observations	11,026	11,026	121,733	121,733
R-squared	0.151	0.199	0.681	0.69

Notes: For the binary and discrete indep. vars. marginal effects are given by exp(b)-1, where b is the regression coefficient. Observations at project level. Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Employer country, worker country and category fixed effects included in all regressions

Table 8 | Country and category fixed effects in the wage and wage bill regressions

	Log hourly wage	Log hourly wage	Log wage bill	Log wage bill
Category fixed effects:				
Category = 11, System	1.024***	0.867***	0.693***	0.618***
Category = 17, unknown	0.937***	0.808***	0.631***	0.561***
Category = 8, Search Marketing	0.904***	0.711***	0.278***	0.206***
Category = 10, Software Development	0.899***	0.687***	0.473***	0.406***
Category = 7, Mobile	0.846***	0.688***	0.299***	0.260***
Category = 3, Creative Arts	0.768***	0.634***	0.282***	0.238***
Category = 14, Video, Photo & Audio	0.750***	0.607***	0.499***	0.443***
Category = 15, Web Development	0.680***	0.494***	0.326***	0.267***
Category = 6, Marketing & PR	0.621***	0.496***	0.311***	0.243***
Category = 13, Tutorials	0.591***	0.405***	0.416***	0.350***
Category = 4, Design	0.582***	0.443***	0.311***	0.262***
Category = 2, Business Support	0.542***	0.398***	0.454***	0.387***
Category = 5, Extraordinary	0.519***	0.449***	0.300***	0.232***
Category = 16, Writing	0.457***	0.360***	0.300***	0.240***
Category = 9, Social Media	0.428***	0.352***	0.117***	0.079***
Category = 12, Translation	0.422***	0.362***	0.124***	0.067***
Country of employer fixed effects:				
Country of employer = 159, Switzerland	0.189	0.130	-0.057***	-0.082***
Country of employer = 41, Cyprus	0.027	-0.008	-0.107**	-0.096*
Country of employer = 18, Belgium	-0.071	-0.070	-0.096**	-0.103***
Country of employer = 11, Austria	-0.045	0.077	-0.141***	-0.121**
Country of employer = 149, Singapore	-0.363***	-0.426***	-0.123***	-0.122***
Country of employer = 55, France	-0.034	-0.044	-0.135***	-0.142***
Country of employer = 118, Netherlands	0.002	0.012	-0.149***	-0.143***
Country of employer = 169, UAE	0.194	0.146	-0.136***	-0.149***
Country of employer = 158, Sweden	-0.101	-0.026	-0.145***	-0.162***
Country of employer = 152, Slovenia	-0.358	-0.174	-0.162*	-0.163*
Country of employer = 43, Denmark	-0.128	-0.194**	-0.161***	-0.164***
Country of employer = 104, Malta	0.225	0.132	-0.166***	-0.165**
Country of employer = 132, Poland	-0.381**	-0.355**	-0.172***	-0.168***
Country of employer = 31, Canada	-0.039	-0.051	-0.169***	-0.172***
Country of employer = 155, Spain	-0.212**	-0.194**	-0.176***	-0.181***
Country of employer = 59, Germany	-0.041	-0.021	-0.190***	-0.187***
Country of employer = 120, New Zealand	-0.086	-0.119*	-0.184***	-0.191***
Country of employer = 171, United States	-0.064	-0.077	-0.187***	-0.192***
Country of employer = 78, Ireland	-0.133*	-0.127*	-0.188***	-0.193***
Country of employer = 10, Australia	-0.073	-0.075	-0.213***	-0.218***
Country of employer = 81, Italy	-0.025	-0.001	-0.201***	-0.218***
Country of employer = 62, Greece	-0.379	-0.350	-0.237***	-0.225***
Country of employer = 42, Czech Republic	0.022	-0.083	-0.244***	-0.231**

Country of employer = 83, Japan	-0.319**	-0.312**	-0.252**	-0.242**
Country of employer = 137, Romania	0.668***	0.739***	-0.292***	-0.276***
Country of employer = 35, China	-0.312*	-0.344*	-0.280***	-0.279***
Country of employer = 28, Bulgaria	-0.382	-0.542**	-0.280***	-0.284***
Country of worker fixed effects:				
Country of worker = 47, Finland	-0.368	-0.428**	-0.273*	-0.262
Country of worker = 48, France	-0.196*	-0.223**	-0.097**	-0.089*
Country of worker = 50, Germany	-0.231*	-0.210**	-0.095*	-0.096*
Country of worker = 38, Denmark	-0.223**	-0.314**	-0.118***	-0.108***
Country of worker = 129, Spain	-0.131	-0.140	-0.166**	-0.168**
Country of worker = 28, Canada	-0.164	-0.145	-0.207***	-0.187***
Country of worker = 85, Lithuania	-0.119	-0.088	-0.215***	-0.207***
Country of worker = 113, Poland	-0.101	-0.103	-0.215**	-0.212**
Country of worker = 133, Switzerland	-0.303	-0.138	-0.252***	-0.235***
Country of worker = 69, Italy	-0.367***	-0.356***	-0.241***	-0.241***
Country of worker = 61, Hungary	-0.411	-0.397	-0.263***	-0.258**
Country of worker = 37, Czech Republic	-0.223	-0.185	-0.327***	-0.306***
Country of worker = 25, Bulgaria	-0.434***	-0.424***	-0.319***	-0.309***
Country of worker = 114, Portugal	-0.183	-0.135	-0.334***	-0.333***
Country of worker = 145, UAE	-0.169	-0.084	-0.357***	-0.336***
Country of worker = 118, Romania	-0.179	-0.144	-0.360***	-0.341***
Country of worker = 36, Cyprus	-0.499*	-0.372	-0.393***	-0.375***
Country of worker = 126, Slovakia	-0.538***	-0.667***	-0.441***	-0.409***
Country of worker = 144, Ukraine	-0.226	-0.226	-0.423***	-0.415***
Country of worker = 71, Japan	-0.294	-0.274	-0.460***	-0.439***
Country of worker = 34, Croatia	0.287**	0.348**	-0.473***	-0.452***
Country of worker = 53, Greece	-0.366**	-0.335**	-0.476***	-0.455***

Note: Fixed effects coefficients from Table 7. *** p<0.01, ** p<0.05, * p<0.1.

We conclude that the characteristics of tasks, workers and employers, as well as their countries of residence, have an impact on the wage and wage bill of a task. Pure price competition in OLMs is limited and non-price qualities of workers matter in the bidding and bid evaluation process. This may alleviate concerns about OLMs as an easy entry gate for cheap labour from developing countries into developed country markets. It also shows that workers from developing countries require good skills and experience in order to be successful in OLMs.

6. THE WELFARE EFFECTS OF OLMS

6.1. Methodological principles

We define overall welfare generated by the OLM as the sum of welfare across all participants in the labour market transaction, i.e., the sum of welfare across workers, employers and the platform. On top of in-platform welfare effects there can be welfare externalities that affect persons not actively participating in the OLM, through the labour market and social security channels. Externalities are discussed in a subsequent section.

Because of limitations in our dataset we can only measure monetized welfare on the basis of differences between online and offline wages, using the average offline wage rate[21] as a benchmark for the opportunity cost for workers and employers. We use overall monthly average wage rates by country before taxes. For the online tasks, we observe average *hourly* wages. To have a comparable measure, we divide average offline wages by 4 (weeks) and then by 40 (hours), according to the ILO measure of average number of hours worked per week. For some countries, we can replace average hourly wages with more detailed sectoral data available from the ILO. For the descriptive statistics in Figures 7 and 8, we match online categories with similar offline sectors for those countries where data is available[22]. However, for the sake of consistency, in the welfare calculations we use overall average offline wages, given the limited number of countries for which sectoral data is available. We are aware of the limitations of using overall average wage rates instead of averages by sector.

Other variables that intervene in the welfare calculations cannot be directly observed or quantified or monetized. We have to make some assumptions on these unobserved non-monetized variables. We invoke the rational choice hypothesis: participants are motivated to participate in OLMs because it increases their welfare. They would not participate if it would have a net negative effect on their private welfare. Consequently, if we observe a negative wage-based or monetized welfare effect in our limited dataset, this is an indirect indication of unobserved or missing non-monetized welfare variables that would probably lift these negative effects into positive territory. Positive wage-based welfare observations may also receive an additional boost from non-monetized variables.

Two sources of welfare effects can be identified. The first major advantage of OLMs is that they reduce search and matching costs between workers and employers. Since these are usually fixed costs, independent of the size of the task, search costs in offline labour markets are often prohibitively high for small tasks. Search costs are deadweight losses that reduce welfare for all parties involved.

[21] We use national gross averages as provided by OECD and several other national sources.

[22] The sectors include: J. Information and communication; K. Financial and insurance activities; M. Professional, scientific and technical activities; N. Administrative and support service activities; and R. Arts, entertainment and recreation

That forces employers to "bundle" tasks until they have a sufficiently large package to recruit an additional worker on a standard contract. When the "bundle" requires a variety of skills it is often difficult to find a worker who matches all the required skills. OLMs reduce these search costs and enable unbundling of tasks. Employers gain because they can recruit a worker with an appropriate skills profile even for small tasks. Workers gain because it allows them to specialise and concentrate on their best skills, increase their labour productivity and earn higher wages. Corporaal and Lehdonvirta (2017) use another classification of benefits for employers, including easier access to scalable sources of labour, skills and expertise; the reduction of start-up and transaction costs and the elimination of conventional hiring barriers. In our view, this classification can be linked to lower entry costs and unbundling.

A second source of welfare is linked to the fact that OLMs eliminate co-location requirements and reduce (but do not necessarily eliminate) geographical trade costs for workers and employers, at least for purely digital tasks that do not require proximity between workers and employers. That eliminates labour productivity-reducing transport costs in a domestic economy setting and enables workers to bridge cross-country productivity and wage differences in a global setting. Workers can realize the labour productivity gains from (domestic and international) migration without incurring the costs of migration (high foreign labour market entry costs, resistance to migration in the country of the employer). Employers benefit from increased competition on the supply side of labour markets that puts downward pressure on wages. Clemens (2011) argues that migration restrictions leave "trillion dollar bills on the sidewalk". While trade in goods, services and capital is relatively free, the estimated trade cost equivalent for labour could be up to 1000% because of immigration restrictions that reflect strong resistance in most destination countries. Trade-in-tasks is often presented as an alternative to migration.

Baghwati (1984) pointed out that migrants move to countries that offer higher wages for their skills. His model of migration distinguishes between three social welfare transmission channels: (a) labour productivity effects induced by migration, (b) quantity and substitution effects in the labour market, and (c) externalities on human capital and other production factors in countries of origin and destination. With our dataset we can partially measure (a) but not (b) and (c)[23]. Regarding (a) we assume that the difference between the offline wage in the country of residence of the worker and the online wage offered by the employer in his country of residence reflects the labour productivity effect from virtual migration.

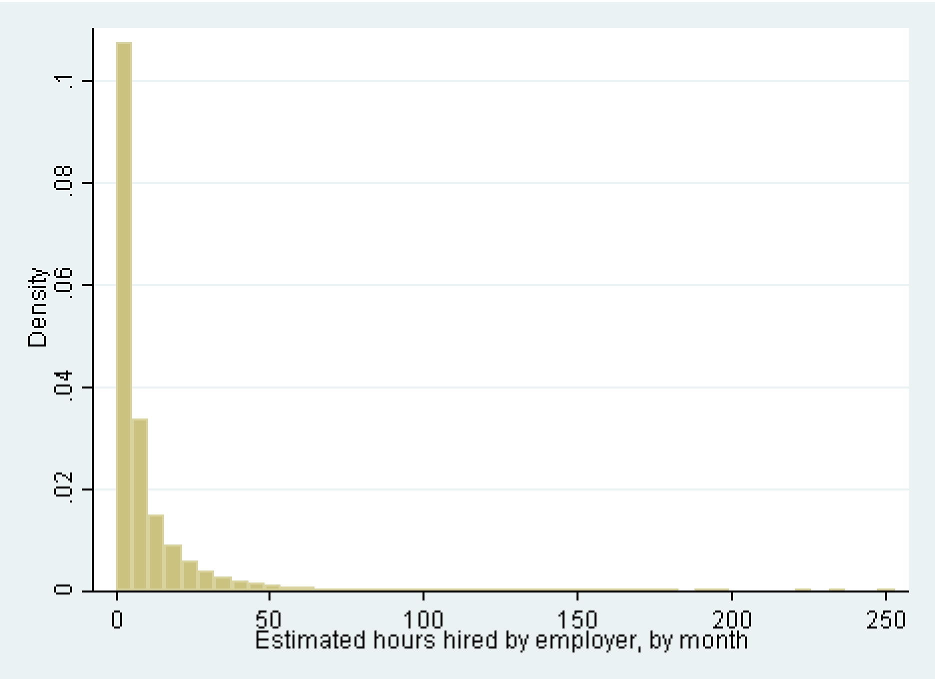
In order to fully comply with (b) we would have to estimate a full set of substitution elasticities in a standard micro-economic model, based on a dataset that would comprise online and offline wage rates and time worked for all workers and employers. It is unlikely that we would ever find such a dataset. Our dataset only includes online wages and working time. We therefore need to make another set of assumptions that enable us to make short-cuts towards the calculation of welfare effects. There are two substitution effects that matter. First, workers can substitute their time between online and offline work. Second, employers can substitute between online and offline workers.

For the first, we take a conservative stance and assume full substitution between online and offline labour by taking the offline average wage rate as the benchmark for the opportunity cost of time. In

[23] It is sometimes assumed that workers work in isolation and there are no learning externalities between workers (Horton, 2017). However, some recent evidence suggests that labour market externalities inside the country of origin can be strong (Khanna & Morales, 2017).

reality, there are several reasons to believe that substitution will be less than perfect. The JRC Digital Labour Markets survey (forthcoming) of OLM workers in the EU shows that online work is more likely to be complement rather than a substitute for offline work. Moreover, the number of hours worked per month in this OLM platform is far below a full time job (Figure 4). Low substitution will reduce the opportunity cost of online work and boost welfare gains from online work. We run a number of alternative simulations to the baseline full opportunity cost scenario that demonstrate the size of these welfare gains. We assume zero substitution between online and offline workers on the employers' side, for several reasons. First, the average task duration is less than 8 hours. Employers would find it costly and difficult to hire an offline worker for such short tasks. Second, monthly aggregate hiring of online workers, even for the top 5% of employers in this dataset, rarely exceeds the equivalent of one working week per month (Figure 5). Employers would find it difficult to hire an offline worker for such a limited amount of time, especially when skills for these tasks would be scattered across different profiles. One would also expect substitution between workers from high and low income countries. However, our wage competition model shows that skills and experience are strong drivers of hiring decisions, more so than wages. The fact that the majority of workers are resident in high income countries supports this argument. Nevertheless, we present some scenario analysis to test the robustness of the welfare effects for non-zero substitution between workers inside and outside the OLM.

Figure 5 | Distribution of estimated hours hired by employers



Note: For the sake of clarity, we exclude in the figure tasks over 100 hours hired, which are less than 1% of the simple in terms of projects and 20% in terms of hours worked. However, we do not make this restriction on the data used in our regressions.

The Bhagwati model assumes that migration pulls up wages in the home country of workers and pushes down wages in the destination country. We cannot measure the impact of OLM wages on offline labour markets. However, taking into account the currently very limited volume of work in OLM, compared to the volume of offline work, we assume that this impact is negligible. The complementarity rather than substitution hypothesis discussed above is consistent with this assumption.

6.2. Workers' welfare

Workers will be motivated to work online when that generates more benefits compared to alternative uses of that time, including leisure and other employment opportunities. An OLM workers survey by Berg (2016) reveals a variety of motives to work online, including (1) earning (additional) income, (2) more flexibility in time allocation and (3) the enjoyment they derive from online tasks. The first suggests a pecuniary motive. The second points to non-work related opportunity costs of time (transport costs, family constraints, etc.) that effectively reduce offline productivity and wages. The third indicates a preference for online work over leisure.

Workers can earn (additional) income online by doing more working hours (quantity of work) and/or working for higher wages. The monetized welfare effect of moving from offline to online work can be measured by comparing online wages with the opportunity costs of offline employment. A possible benchmark for measuring workers' opportunity cost is offline wage income, provided the worker has an alternative offline job. In an ideal world all the required data would be available and we would estimate substitution elasticities between alternative time uses. That would give us an overall measure of the opportunity cost of time, an average across all workers in the sample. We do not have all this information on the platform workers. We therefore need to apply some simplifying assumptions. The first simplifying assumption is to replace workers' individual offline opportunity wage rates by the average offline wage rate in their country of residence. The average wage rate will be too low for some, too high for others. Our assumption is that on average we get it right. Taking offline wages as the opportunity cost benchmark implies that we assume full substitution between online and offline work. In reality, substitution will only be partial. Offline jobs are not always available for workers, or they may prefer an online over an offline job for other reasons not related to wages. As such, this assumption is conservative because it overestimates the opportunity cost of time and underestimates the welfare benefits from online work. Later on we carry out sensitivity tests to explore how variations in this average offline wage assumption affects our welfare estimates.

The actual calculation of welfare requires several steps. We observe the online wage bill but not working hours for a specific task. To calculate this, we combine information from (a) the agreed hourly wage sample (11,157 tasks) and (b) the agreed wage bill sample (122,998 tasks). We benefit from the fact that 57% of the wage bill tasks were carried out by workers for which we also observe agreed hourly wages in the wage sample. If they completed several tasks we take their lowest hourly wage from the wage sample. Then, for a given task, we calculate the estimated number of working hours by dividing the agreed wage bill by the lowest hourly wage of the worker. Once we have determined the duration of a task, we multiply this by the offline average wage in the worker's country of origin to calculate the offline wage bill of the task. We then subtract the offline wage bill and the fees paid to the platform from the actual online wage bill to get a first estimate of workers' welfare benefits from working online in the platform. Fees contribute to the welfare of the platform organizer. They are paid in full by the workers. Employers do not pay any fee.

For each job performed on the platform, the effect of OLM on workers' welfare is then given by:

$$ww_i = (W_{on} \times Q_i) - (W_{off} \times Q_i) - f_i = (W_{on} - W_{off}) \times Q_i - f_i \quad (3)$$

where ww_i is the worker's wage-based monetized welfare derived from project i; W_{on} is the online hourly wage rate, W_{off} is the offline average hourly wage rate; Q_i is the estimated number of hours worked for the specific project i and f_i is the fee paid to the platform.

This simple welfare function revolves purely around wages. It does not cover unobserved variables in our dataset such as benefits not related to wages and thus not directly monetized in the platform. For example reduced transport costs and avoided (domestic and international) migration costs, more flexible working hours and compatibility with family constraints, etc. will further increase welfare. Welfare externalities such as private benefits from shirking on contributions to public welfare by avoiding taxes and social security contributions are dealt with in Section 6.6.

6.3. Employers' welfare

Employers benefit from lower market entry and search costs in OLMs that enable them to unbundle tasks. They will outsource tasks to an OLM if it enables them to save labour costs, subject to a quality standard, or if it enables them to carry out tasks that they would otherwise not get done. This allows them to find worker profiles that better match the requirements of specific tasks. It increases the division of labour and boosts labour productivity.

We only observe the cost side of the employers' profit function, i.e. the online wage bill paid to the worker. We do not observe the revenue side or other benefits that the employer derives from having the project completed. For instance, employer' benefits from unbundling tasks are not directly observable. Given this limitation, we calculate employers' monetized welfare as savings in labour costs by comparing the online wage with the average offline labour cost (wage plus employer social security contributions) in the country of residence of the employer. Rather than trying to find an "equivalent worker labour cost" for each skills profile we follow the same reasoning as we applied above to workers and take the average offline labour cost in the country of residence of the employer. Again, this will be too high for some tasks, too low for others, but we assume that, on average, we get it right. We are aware that we use different measures of wage for the calculation of employers and workers welfare[24] -for the employers we include the amount paid to the social security system whereas for the worker we do not include the extra benefits he receives from the respective national social security system (if any), only the gross wage. However, given the data available we think this is the most correct option. Calculating the national social security for workers would require further assumptions and extra information that we do not have.

We decompose the agreed wage bill into wage and estimated working time. For the alternative offline scenario, we obtain total employment cost for a given task by multiplying the hours worked with the hourly employment cost (wage plus employers' contributions) in the country of residence of the

[24] See OECD for further definition on wages and labour costs: https://stats.oecd.org/mei/default.asp?lang=e&subject=11

employer. At the individual employer project level, the effect of OLM on employers' welfare is then given by:

$$ew_i = (LC_{off} \times Q_i) - (W_{on} \times Q_i) = (LC_{off} - W_{on}) \times Q_i \quad (4)$$

where LC_{off} are the hourly labour costs in the country where the employer is located[25]; W_{on} is the online hourly wage rate paid by the employer and Q_i is the estimated number of hours worked for the specific project. This method assumes that offline execution of a task is a realistic alternative. It also assumes that the revenue that an employer obtains from a completed task is independent of whether it is completed offline or online.

It is worth noting that we use different definitions of wages for the worker and for the employer. We understand that this could be a drawback of the data.

6.4. The OLM platform

We do not observe the complete profit function of the platform. Since we do not observe platform production costs, we calculate platform benefit as the aggregation of all fees generated by all projects. Note that this is an overly optimistic assumption on platform welfare. Actual welfare will be lower than gross revenue because (unobserved) operating costs have to be deducted. Under the rational choice hypothesis, we assume that the platform as a commercial profit-maximizing company would only operate if (expected long-run) profits are positive. The actual monetized welfare of the case study platform will thus be somewhere between zero and the observed fee revenue. The fee structure consists of a 20% fee on earnings per worker up to 520 €/month and 5% thereafter.

6.5. Results

Monetized (wage-based) and non-monetized (unobserved) welfare effects are presented in Figures 6a/b/c and Tables 9a/b. Results are broken down by region. UK-UK only considers tasks posted by employers and completed by workers located in the UK, i.e. no international trade-in-tasks. The EU-EU perspective considers tasks traded between employers and completed by workers located anywhere in the EU. The third group includes tasks traded between employers located in high income countries and completed by workers in low income countries[26]. Note that only 3.7% of all employers are located in low-income countries. The last category aggregates the worldwide welfare impact of the platform for workers and employers located anywhere in the world.

[25] Note that employers do not pay any fee to the platform.

[26] We use the World Bank classification for low and high income countries. Upper middle income countries are grouped with high income, lower middle income with low income countries.

Figure 6a | Total welfare effects by region (M €)

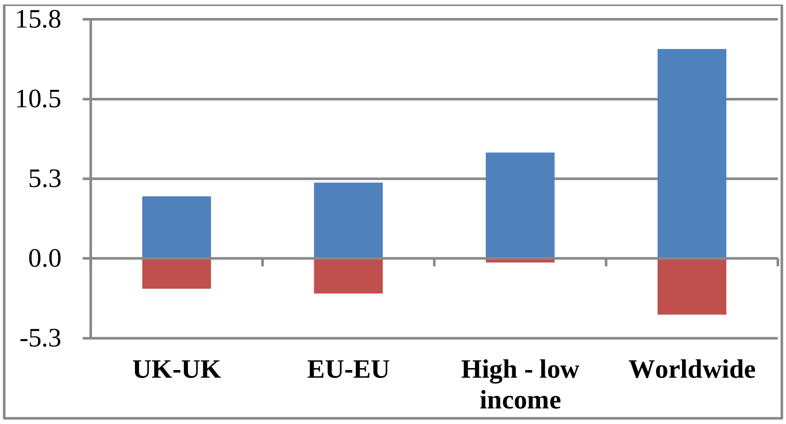


Figure 6b | Employers' welfare by region (M €)

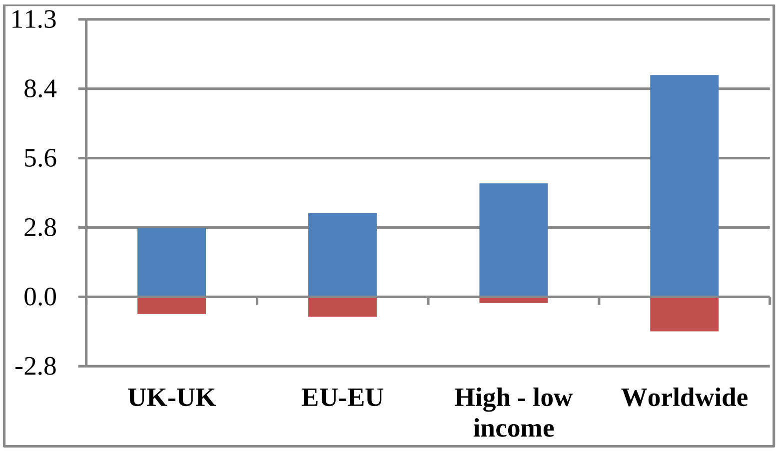


Figure 6c | Workers' welfare effects by region (M €)

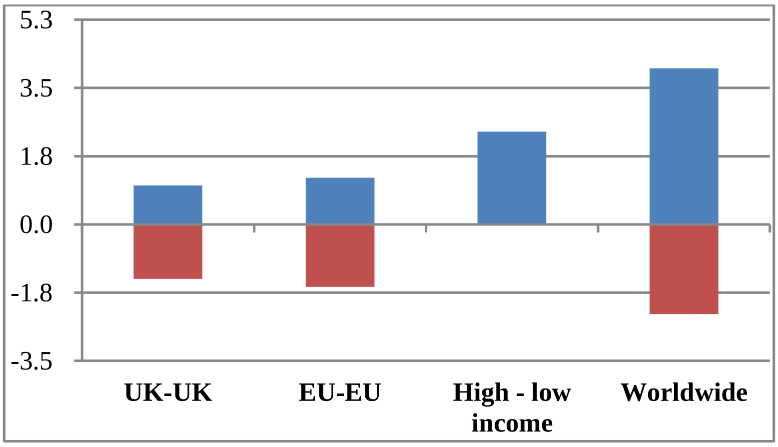


Table 9a | The magnitude of welfare effects for employers, workers and the OLM platform (M € and percentage of wage bill)

Employer region - worker region	(1) Paid wage bill (M€)	(2) Total welfare (M€ / %)	(3) Employers (M€ / %)	(4) Workers (M€ / %)	(5) Platform (M€ / %)
UK-UK	4.9	2.1	2.1	-0.4	0.4
		42.4%	*42.9%*	*-7.7%*	*7.2%*
EU-EU	5.9	2.7	2.6	-0.3	0.4
		45.9%	*44.2%*	*-6.6%*	*7.3%*
High - low income	3.2	6.9	4.4	2.4	0.2
		214.6%	*62.7%*	*54.4%*	*9.2%*
Worldwide	10.7	10.1	7.5	1.8	0.8
		94.0%	*70.4%*	*16.8%*	*7.2%*

Note: Aggregated welfare in million EUR for the indicated region and by type of participant; percentage over wage bill. Welfare effects are calculated using average offline wages / labour costs in the country of residence of workers and employers. See section 6 for further details.

Table 9b | Share of welfare by OLM participant and region

Region	Total welfare (M€)	Employers' welfare	Workers' welfare	Platform welfare
UK-UK	2.1	101.2%	-18.1%	16.9%
EU-EU	2.7	96.2%	-12.0%	15.9%
High - low income	6.9	63.0%	34.3%	3.2%
Worldwide	10.1	74.9%	17.4%	7.6%

Note: Welfare effects are calculated using average offline wages / labour costs in the country of residence of workers and employers. See section 6 for further details.

Table 9c | Worker welfare, sensitivity analysis with respect to the average offline wage assumption

Average/min/unemployment weights	Worker welfare (M€)	% of overall welfare	Overall welfare (M€)	Share of projects with positive worker welfare
100/0/0	1.75	17.4%	10.06	61.3%
50/50/0	5.85	41.3%	14.16	74.4%
0/100/0	7.30	46.8%	15.61	98.0%
0/0/100	9.94	54.5%	18.25	100.0%

Note: We include in this table the overall effects. Total wage bill is 10,711,203€. Total number of projects is 69,511. Each row represents a different linear combination of the alternative offline scenarios.

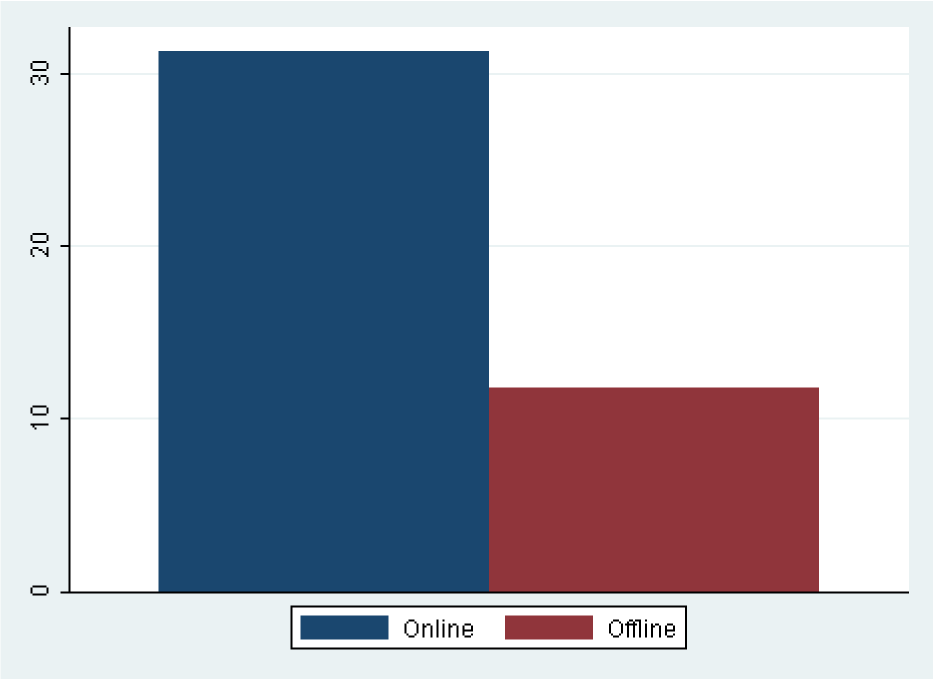
Overall, the platform generated about 10.1 M€ in worldwide monetized welfare or 94% of the total worldwide wage bill of 10.7 M€. Employers made savings in wage costs of about 70%, compared to what they would have paid if they would have been able to hire offline workers in their country of residence to carry out these small tasks. Workers earned about 17% more than what they would have earned if they spend the same time working offline. The platform earned 7% of the wage bill in gross fee income. In summary, 75% of the wage-based welfare benefits accrued to employers, 17% to workers and nearly 8% to the platform itself.

Figures 6a/b/c present both the monetized and non-monetized welfare gains (the blue and red bars). The non-monetized gains are presented as a negative residual because they represent cases where workers earn less online than what they could have earned offline at the average local wage rate in their country of residence. By virtue of the rational choice hypothesis however we assume that there are good reasons why workers choose this situation and that these reflect non-monetized welfare benefits rather than costs. They are unobservable benefits in our dataset. They essentially arise in labour market transactions inside the UK and the EU, between high-income countries. They disappear when employers are located in high income countries and workers in low income countries. Since our method to calculate welfare is based on comparing wages in the country of the employer and the worker, differences in income or GDP per capita drive the results. We conclude from this that workers in low-income countries are probably more motivated by labour productivity and wage gains while workers in high-income countries will derive more motivation to participate from non-observed factors such a time flexibility and avoided transport costs (see below).

Figures 7, 8 and 9 illustrate this. Figure 7 shows that the worldwide average of online wages in the platform is almost 20 €/hour higher than the offline average wage[27]. Figures 8 and 9 show however that online workers in high income countries would still be better off if they could work at the average offline wage in their country of residence. This explains why many UK and EU workers experience negative welfare effects when working online. Still, they may have other incentives than wages to move online that we will discuss below. Workers in low income countries find a wide gap between local offline wages and available online wages. It can reach 20 €/hour on average. That explains why, at worldwide level, the total welfare effects get strongly positive. Figure 8 shows how the ratio of offline to online wages varies across countries. Lower-income countries are situated to the left-hand side where the ratio is considerable below 1. These workers have an incentive to migrate online. Higher-income countries are situated to the right-hand side where the ratio reaches 1 or (slightly) above 1. Figure 9 shows that these deviations are correlated with GDP per capita in the country of residence of the worker.

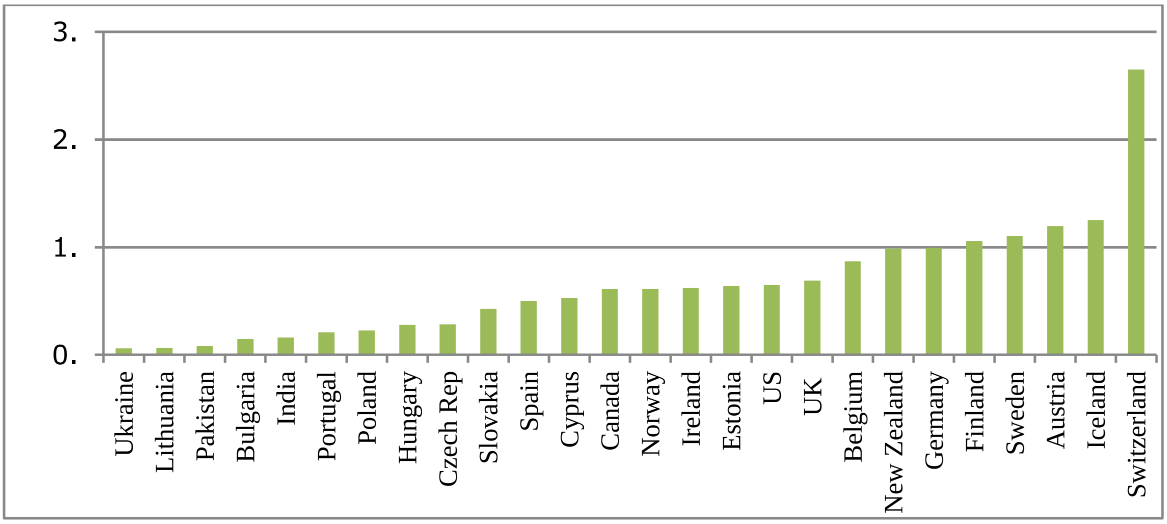
[27] See section 6.1 for further detail on the offline sectors included in this comparison.

Figure 7 | Online vs offline average hourly wages, EUR



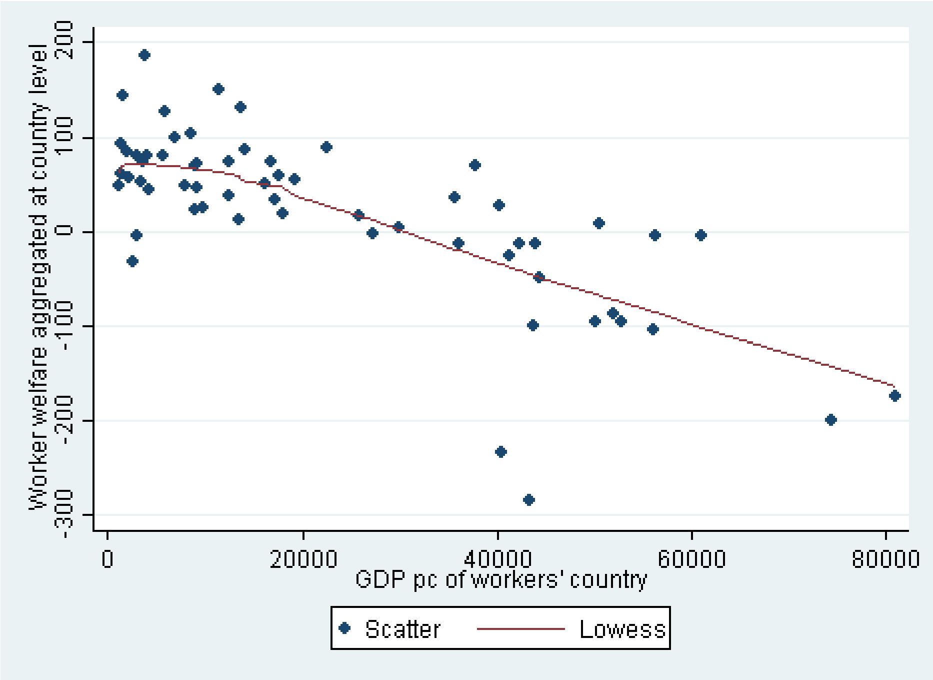
Note: Average online include expected wages from PPH. Offline hourly earnings calculated from ILO data for those sector matching online tasks.

Figure 8 | Ratio of offline to online wages (in €/hour)



Source: ILO and data provided by PPH.

Fig 9 | Workers' welfare in a country vs GDP pc



Note: Workers' welfare is defined as the online wage bill minus the wage bill that a given worker would have had received offline in his country of residence. The four "outlier" countries in the lowest part of the graph are, from left to right, United Arab Emirates, Canada, Norway and Switzerland.

Figures 6a/b/c are based on the conservative assumption that the average wage rate in the country of the workers reflects their opportunity cost of time. Lowering the opportunity cost of time of workers will boost their monetized welfare benefits and lift up the bars. We carry out a number of sensitivity tests around this conservative baseline assumption in Table 9c where we consider two alternative opportunity costs of workers' time hypotheses: the minimum wage rate and a zero opportunity cost of time for unemployed workers. We calculate two intermediate scenarios where we vary the weight of these alternative assumptions (Column 1) on the opportunity cost of time, from 100% based on the average wage rate (the assumption underlying Table 9a) to the other extreme, 100% zero opportunity cost of time. These alternatives give a boost to the welfare effects. Workers' share in total welfare ranges from 17.4% in the baseline scenario to 54.5% in the most optimistic scenario.

We can apply similar reasoning to welfare effects for employers. Overall, employers benefit from monetized welfare effects when comparing offline to online wages. That is, they save money on their wage bills by moving tasks online. Even inside the UK and the EU, employers benefit considerably from hiring workers online, in the order of more than 40% on top of their wage bill (on average across all tasks and based on the average offline wage rate). Employers benefit even more from the wide wage gaps between high and low income countries. This gives a further boost to their welfare effect to 74% on top of the paid wage bill. We also find that in 25.5% of all cases employers pay more online than the average offline labour cost, i.e. individual employer welfare at the task level is negative. Following the rational choice hypothesis we assume that employers will only hire workers up to the point where the marginal cost (wages) equals marginal revenue derived from workers' output. We do not observe employers' marginal revenue in our dataset but we assume that it is always larger than or equal to the wage rate, even when an employer pays more than the average offline labour cost. We attribute these to unobserved benefits from task unbundling that are not monetized in terms of wage savings. They may however be monetized elsewhere in the employer's profit function though we cannot observe that in the data. Productivity is higher than average because unbundling enables employers to hire a specialist for a small task who will perform better than a less specialised offline worker who is hired for a larger bundle of tasks.

6.6. Welfare externalities

So far we have looked at welfare effects among participants in the OLM: workers, employers and the platform itself. There may also be welfare externalities on the rest of society. There are several potential transmission channels for externalities.

The first runs through offline labour markets. We assume that the volume of labour absorbed by OLMs is small compared to offline labour markets and therefore has no impact on offline wages. That neutralises externalities between online and offline workers through the price (wage) channel. On the other hand there may be some degree of substitution in labour quantities between online and offline labour. We have assumed full substitution in our labour opportunity cost assumption but pointed out that this is most probably an overestimation. We have no data that would allow us to estimate the actual degree of substitution.

Another welfare transmission channel on the rest of society runs through the social security system which we define as including, amongst others, unemployment insurance, healthcare and pensions. As in most OLMs, in our case study employers do not contribute to workers' social security. Workers are considered to be self-employed and should pay their taxes and make their own social security contributions in compliance with laws and regulations in their country of residence, as explained in the Terms and Conditions for working in this OLM platform[28]. In some countries there are no mandatory individual social security contributions for self-employed, only voluntary schemes. The state (all taxpayers) may provide basic social security and pay the cost from general tax revenues. Some OLM workers may free-ride[29] on social security coverage linked to offline jobs that they hold or to benefits schemes of family members. To the extent that society at large (through public social security systems) pays (part of) the social security bill, externalities can emerge when workers shirk on mandatory contributions. That transfers part of the welfare costs to other taxpayers but it does not necessarily affect the total cost of social security or total welfare in the country of residence of the workers. It should however be deducted from the private welfare benefits generated inside the platform. There are major problems with the estimation of these externalities, mainly because we have no information on workers' tax payments and social security contributions. Social security rules and regulations for self-employed workers vary widely across countries. Collecting that information would go far beyond the purpose of this research project.

Another problem with social security contributions for self-employed workers in OLMs is that most administrative systems are not designed for to match the flexibility and very low labour market entry and exit costs in OLMs. A social security system adapted to this type of labour market would have to operate with very minimal entry and exit transaction costs, presumably in a purely digital setting without paperwork.

[28] With respect to workers, the platform explicitly mentions in the Terms and Conditions that *"you* [the worker] *promise you have made and will make all required legal and tax filings. If relevant, you will file all necessary legal documentation relating to your self-employment required by any governmental body, and pay all applicable taxes including without limitation or other income tax and national insurance*".

[29] Free-riding only occurs when contributions are meant to be proportional to earnings.

There are no easy solutions to introducing more regulatory standards with regard to social security and other labour conditions that would apply to global OLM. As mentioned in the introduction there is a debate on the legal status of platform workers in the "gig economy" and whether they should be given employee status in a platform. The Uber debate is not applicable to digital task OLMs because they do not require physical proximity between workers and employers; they often live in different countries. Proximity creates clarity with regard to which country's rules apply, including rules on employment status, apply because both parties reside in the same country. The rules regarding self-employment status of that country apply. However, for example, when an Indian computer programmer works for a US company, intermediated by a UK-based OLM, there are doubts as to which rules of (self-) employment determine the employment status of that worker: UK rules, US rules or Indian rules? The recently revised EU Posted Workers Directive does not offer a solution because workers do not move from one country to another[30]. Moreover, India is outside the EU and EU directives do not apply there. There are no ILO international labour standards either that could clarify this situation.

7. CONCLUSIONS

The welfare effects of global trade in purely digital tasks in Online Labour Markets (OLMs) are fiercely debated. Some studies take a rather critical view and focus on job fragmentation and qualitative changes in working conditions while others emphasize the economic opportunities that OLMs generate. The present study seeks to quantify some of these effects, both in terms of labour market fragmentation, or unbundling in economic jargon, and opportunities for income gains for workers and cost savings for employers. In particular, we explore (a) the drivers of global trade in digital tasks, (b) the determinants of online wages and (c) the economic welfare effects of OLMs.

Trade-in-tasks is a well-known concept in the international trade literature. It involves workers who embody their skills in physical goods that are shipped from their country of residence to the country of destination. Digital OLMs give new meaning to trade-in-tasks. There are no physical goods to be shipped, only digital files at virtually zero transport costs. In our case study of a medium-sized UK-based OLM, we find that almost 60% of all tasks are outsourced to workers outside the country of residence of the employer, though that percentage varies by type of tasks. Employers mostly reside in higher-income countries (89% are based in the UK, the EU and the US) while workers are mostly in lower-income countries. This shows the importance of OLMs as a conduit for online virtual migration of workers.

Geographical trade costs are not entirely eliminated however. Despite the global nature of digital OLMs, there appears to be some degree of home bias. Geographical and cultural distances continue to play a role. The platform is based in the UK and that is also its main market: 46% of all workers and 68% of all employers reside in the UK. Strong ties between the UK and India are apparent in the trade matrix which suggests the importance of ethnic ties. We find that a wider difference in GDP per capita has a negative impact on trade in tasks: the wider the economic gap between the country of the worker and the employer the harder it is for workers to get into that market. However, income gaps reflect skills gaps between countries. Workers' skills

[30] EU rules on social security only clarify which country's social security applies to a worker when working in another country. The recently approved modifications to the EU Posted Workers Directive clarify that the social security rules of the country where the work is carried out apply, not the country of residence of the worker. However, this is not applicable to digital services tasks in OLM because workers do not physically move from their country of residence to the country of the employer. Consequently, as long as OLM workers are self-employed their home country rules apply. See Social security systems in the EU. http://europa.eu/youreurope/citizens/work/unemployment-and-benefits/social-security/index_en.htm

and experience drive hiring decisions. These qualities may be more abundantly available in high-income countries. That diverts trade towards these countries.

We examine market entry conditions for workers and employers. Workers pay a digressive entry fee while employers have free entry. Moreover, employer entry is subsidized in the sense that they benefit from the public goods nature of worker review scores produced by previous employers. Especially the first review scores are important for a worker to gain effective market access. Review scores combined with digressive entry fees increase the cost of multi-homing for workers and bind them to the platform. That, in turn, makes them more vulnerable to increased entry costs. Intermediaries could decrease worker entry costs by subsidizing the production of public worker quality signals.

Global virtual migration opens the door to direct competition between workers from low- and high-income countries and raise concerns about OLMs as an easy entry gate for cheap labour from developing countries into developed country markets, triggering a race-to-the-bottom in wages. Our findings nuance this assessment. The characteristics of both workers and employers, as well as their countries of residence, have an impact on wages. Notably, pure price competition in OLMs is limited; only about half of all deals are settled at the lowest price bid. The other half is settled at prices above the lowest bid, which indicates heterogeneity in the labour market. Workers' skills and experience as well as their countries of residence, have an impact on the probability to be hired as well as on the agreed wage rate. Worker quality signalling via review scores induces superstar effects and a very uneven distribution of work. The top-1% workers receive 27% of the total wages paid in the platform. They are more frequently hired and work on larger projects. This very uneven distribution of transactions has been observed in many online markets and is a direct result of lower digital information costs (Bar-Isaac et al., 2012). The platform imposes a minimum wage rate of 6£ per hour, slightly below the official UK minimum wage of £6.70/hour. Worldwide, only 3% of all tasks were paid below this minimum wage rate. Many workers and employers on the platform are not UK residents. This raises the question to what extent UK minimum wages would apply to them.

There are two main drivers for welfare effects in OLMs. First, OLMs are two-sided digital markets. They bring together large numbers of workers and employers; reduce labour market entry costs and lower matching costs between potential employers and workers – compared to offline labour markets. Lower fixed matching costs facilitate task unbundling, or job segmentation. That, in turn, further improves skills matching and increases labour productivity. Second, trade in digital tasks reduces geographical constraints and costs related to geographical proximity between workers and employers. It reduces the costs of moving workers around and enables virtual domestic and international migration. These drivers increase labour productivity and wages for workers and result in labour cost savings for employers. Both sides of the market gain from these arrangements.

We estimate the monetised welfare benefits that workers and employers derive from participation in OLMs based on differences between online and offline wages in the country of residence of workers and employers. Other non-monetised sources of welfare gains such as more flexibility for workers and task unbundling for employers remain unobserved in our limited dataset. Based on wage data and using panel data spanning a period of 24 months, we find empirical evidence that this OLM has positive monetary welfare effects, both for workers (+17%) and employers (+70%). Because we have no information on workers' alternative employment opportunities and cannot estimate the rate of substitution between online and offline work, these calculations are based on a conservative opportunity cost assumption whereby all OLM work is assumed to fully substitute for offline work at the average wage rate in the workers' country of residence. Less conservative sensitivity tests around that benchmark show substantial increases in monetised welfare reaching 40-50% welfare gains for workers. A majority of the 39% of workers who receive an online wage below the average wage rate in their country of residence are residents in high-income countries. While they experience negative monetised welfare effects in our wage-based calculations, the rational choice hypothesis suggests that they are likely to derive other (unobservable) non-monetised benefits from working in OLMs, such as flexible time use and savings in transport/migration costs, or that they face a lower-than-average opportunity cost of time, for instance when they are unemployed.

We find strong monetised welfare gains for employers, in the order of 40-70% of wages paid to workers. Employers' gains stem mostly from lower wage costs compared to average wage in their country of residence. The vast majority of employers (>96%) is located in high-income countries and hire many workers from lower-income countries. The rational choice hypothesis suggests that employers who pay more than the average wage in their country of residence (25% of all cases) and experience negative monetised welfare effects will still derive (unobservable) non-monetary benefits from hiring workers online, for instance because it enables them to unbundle tasks and hire more specialized workers for small tasks, or more skilled workers than available on the local labour market. The data show the extent of unbundling: the median duration of tasks is only 3.5 hours; the average 7.9 hours.

Of course, these potential wage-based monetary welfare effects have to be balanced against less favourable working conditions in OLMs in terms of social security, employment stability and other non-wage benefits, when compared to standard working conditions in offline labour markets. OLMs have enabled global virtual online labour migration. They span many national labour markets and social security systems. Transaction costs associated with existing offline social security and labour market regulation and administration may not be adapted to digital OLM with very short-term tasks and very low entry and exit costs. Workers with self-employment status are bound by the relevant regulations in their home country. Attempts to give employee status to global OLM workers would be challenging because these OLM span a wide variety of national regulatory systems.

For the time being, the relative importance of digital OLMs remains rather limited compared to offline labour markets. Some authors even claim that these markets might eventually disappear (Stark 2017). However, it is quite plausible that they will rapidly grow in importance. That would expose the divergence in conditions in online and offline markets and increase pressure towards harmonisation, not only within countries but also between countries.

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