The International Price of Remote Work*

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Abstract

We study how the price of remote work is determined in a globalized labor market using data from a large web-based job platform, where workers from around the world compete for remote jobs. Despite the global nature of the platform, we find that remote wages are higher for workers in regions with higher income per-capita. This correlation is not accounted for by differences in workers' observable characteristics, occupations, or differences in the employers' locations. Instead, data on wage-histories indicate that remote wages are partly determined by the conditions that workers face in their local labor markets. We also show that remote wages expressed in local currency move strongly with the dollar exchange rate of the worker's country and are highly sensitive to foreign competition. Finally, we identify occupations at high-risk of being offshored based on the prevalence of cross-border contracts.

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JEL Codes: F1, F2, F4, F6

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1 Introduction

An increasing number of jobs are being done remotely, a trend that accelerated dramatically during the COVID pandemic.[1] Remote work can be done from anywhere, even across international borders, which can make these jobs easier to offshore.[2] By globally integrating labor markets, the rise of remote work can have a profound impact on the levels and dynamics of wages across the world.[3] Will wages be equalized across remote workers located in different countries? How will such wages respond to international shocks? Which remote jobs are more likely to be offshored? While these questions are crucial for understanding the future of wages in both developing and developed countries, there is limited research on how the price of remote work is determined in globalized labor markets.

This paper uses new data from a large web-based job platform to shed light on these questions. Web-based job platforms match employers and workers located around the world who trade tasks that are delivered remotely, providing a window into a globalized market for remote work. The number of such platforms has tripled over the past decade. By 2020, hundreds of web-based job platforms had facilitated millions of international transactions totaling over 50 billion US$ (ILO 2021). The emergence of these platforms coincided with the dramatic growth in ICT-Enabled Service trade, which quadrupled in the US since the year 2000 and now accounts for 70% (800 billion US$) of all US service trade.[4]

Our dataset is sourced from one of the largest platforms in the market today. It has several features that make it particularly well suited for our purposes. First, workers are located around the world and compete for the same jobs. These jobs can be done remotely, require little capital other than a computer, and encompass a wide range of occupations, ranging from accountants to web developers. This makes the platform the ideal marketplace for studying the international price of remote work. Second, the dataset is very rich: in addition to hourly wages, it contains extensive information on worker characteristics such as experience, earnings, quality ratings, and standardized test scores and certifications. This information is essential for understanding cross-country wage differences, as it facilitates the comparison of workers around the world. Third, the data record the workers' job histories in the platform (wages, earnings, and start date of each job), which are necessary

[1] Bloom et al. (2022), Aksoy et al. (2022), and Hansen et al. (2022).

[2] Blinder and Krueger (2013).

[3] Baldwin (2016, 2019) and ILO (2021).

[4] U.S. Bureau of Economic Analysis, Table 3.1. International Services (accessed Sept 30, 2021).

for understanding how remote wages respond to shocks. Finally, the job histories contain the employers' identities and locations, which in conjunction with the workers' locations, allow us to identify which jobs are being offshored.

We first document large differences in remote wages across workers located in different countries. For example, the wages of Indian workers are, on average, a third of those of US workers. In fact, the country of the workers accounts for at least a quarter of the variance of wages in the data. Furthermore, remote wages are strongly correlated with the GDP per capita in the worker's country: the elasticity of wages to GDP per capita is 0.22. We document a very similar elasticity between remote wages and GDP per capita across US states. These elasticities are not accounted for by observable differences in worker and job characteristics, differences in the employers' locations, or the fact that workers work for different employers. We show, however, that remote wages are more equalized across countries than non-remote wages.

We propose a model of a global remote labor market that rationalizes these observations. In the model, workers from different locations are imperfect substitutes and can choose to work either in their local or in the remote labor market.[5] Equilibrium remote wages vary across locations if workers have different productivities or face different local wages. We disentangle these two alternative hypotheses by estimating a model-based exchange rate pass-through (ERPT) regression. We show that the partial elasticity of dollar wages with respect to the exchange rate between the dollar and the currency in the worker's location is 0.20, which is in line with the cross-country elasticity of remote wages to GDP per capita. Under the assumption that changes in exchange rates affect local wages denominated in dollars but are uncorrelated to changes in remote workers' productivity, this result indicates that remote wages are tied to the conditions that workers face in their local labor markets.

We also study how remote wages respond to other international shocks. Our estimates imply that (partial) ERPT into local currency wages is 80%. This is in sharp contrast to non-remote wages, which typically do not respond to movements in exchange rates at short horizons.[6] We further show that a worker's wage reacts strongly to changes in the wages of other workers on the platform. Guided by the model, we regress the change in a worker's wage on an index measuring the changes in wages of a worker's competitors. To overcome endogeneity issues, we exploit that workers in different sectors face com-

[5] Alternatively, we can assume that workers are perfect substitutes but specialize in different tasks, as shown in Appendix A.4.

[6] This finding is not mechanically accounted for by remote wages being sticky in dollars, as we obtain a similar elasticity when focusing on a subsample of dollar wages that do change in a particular period.

petitors from different countries, and construct a model-based instrument for changes in competitors' wages that uses variation in the inflation and exchange rate changes in the competitors' countries. We find that workers adjust their wages in response to changes in their competitors' wages with an elasticity of 0.74. Since most of our workers work from outside the US, this means that US remote workers are exposed to shocks that affect their foreign competitors.

Finally, we use our data to shed light on which occupations are more likely to be offshored. Existing measures of 'offshorability' typically hinge on subjective judgments of the different attributes of a job. Such judgments are often based on whether a job can be performed remotely. For example, Blinder and Krueger (2013) establish that a job is easily offshorable if it involves extensive use of computers/email, processing information/data entry, talking on the telephone, or analyzing data. Instead, we directly measure the frequency with which US jobs are offshored by computing the share of US contracts in an occupation in which the worker is located outside the US. The data on cross-border contracts reveal that whether a job is done remotely is an imperfect proxy for whether a job is actually being offshored. For instance, less than a third of grant writer jobs in the platform are offshored, even though all of them are performed remotely. We show that wages are less dispersed across countries in occupations that are more frequently offshored.

Our paper relates to various strands of the literature. First, it is related to a rapidly growing literature that studies the rise of remote work and its consequences. Hansen et al. (2022) document a three-fold increase in vacancy postings for remote work between 2019 and 2022. Aksoy et al. (2022) use data from 27 countries to document work-from-home patterns around the world in 2022. Barrero et al. (2022) use survey data to estimate that remote work can moderate wage-growth pressures in the US by 2 percentage points over two years.[7] We contribute to this literature by documenting cross-country differences in wages across workers in a globalized market for remote work.

Second, we contribute to a large literature on international price and wage comparisons. The main source of international price comparisons is the Penn World Table (see Feenstra et al. 2015), while more recent papers make international price comparisons using online data (see, e.g., Cavallo et al. 2014, Gorodnichenko and Talavera 2017, and Cavallo et al. 2018). Data on international wages are more limited. Ashenfelter (2012) documents

[7] There is a separate literature that uses data from remote job platforms to study topical questions in Labor Economics. Horton (2017) and Barach and Horton (2021) use experimental data from a large platform to study how minimum wages and compensation histories affect labor market outcomes. Stanton and Thomas (2015) use data from oDesk (now Upwork) to show that outsourcing agencies that intermediate between workers and employers have emerged in that market, while Dube et al. (2020) use data from Amazon Mechanical Turk to study monopsony power.

cross-country wage differentials for McDonalds' employees. Hjort et al. (2019) document that multinationals' wages around the world are anchored to wage levels at headquarters, while Hjort et al. (2022) use a database covering compensation for 300,000 middle managers to show that their wages vary little across countries. Inside the US, Hazell et al. (2022) show that large firms post similar wages across locations. We contribute to this literature by providing international wage comparisons for remote workers. We show that despite the global nature of this marketplace, there is pervasive dispersion in wages across observationally-equivalent workers that are located in different countries.

Third, our paper contributes to an extensive literature on exchange rate pass-through (see Burstein and Gopinath 2015 and the papers cited therein). Gopinath et al. 2020 show that in most countries, goods export prices in dollars are stable, and local currency export prices move with the dollar exchange rate. Due to data limitations, that literature has focused almost exclusively on exchange rate pass-through into goods prices. Our paper is the first to study pass-through into the price of tradeable services (remote jobs). We show that ERPT into dollar wages is low, so remote wages denominated in domestic currency move almost one-to-one with the dollar exchange rate. In this respect, the global market for remote workers behaves similarly to the global goods market.

Finally, our paper is related to a large literature on how wages are affected by foreign competition, either through trade (e.g. Goldberg and Pavcnik 2007, Autor et al. 2013, 2016), offshoring (e.g. Feenstra and Hanson 2003, Hummels et al. 2014), or international migration (e.g. Borjas 2014, Card and Peri 2016). Blinder (2009) and Blinder and Krueger (2013) classify occupations according to their offshorability, and consider jobs that can be done remotely as being easily offshorable. Our paper lies at the intersection of these topics, as the cross-border contracts in our platform can be simultaneously interpreted as trade in services, offshoring, or 'tele-migration'. We show that in a globalized market for remote work, a worker's wage responds strongly to changes in the wages of foreign competitors. We also measure the prevalence of cross-border remote work for different occupations, and document substantial heterogeneity in the frequency at which remote work is offshored across remote occupations.

The rest of the paper is organized as follows. Section 2 describes the data. Section 3 compares remote wages across countries. Section 4 studies how remote wages respond to international shocks. Section 5 measures which jobs are more frequently offshored, and the last section concludes.

2 Data

2.1 Data description

Web-based job platforms match workers and employers across the world who sell and buy services that are delivered online. We obtained our data from one of the largest web-based job platforms in the market today. We collected one snapshot in January 2019 and another in November 2020. The platform encompasses remote jobs from a wide range of industries, ranging from accountants to web developers, and has millions of registered workers and employers around the globe that transacted around 2 billion US$ in 2020.

Workers that register on the platform must create a profile and post an hourly wage at which they are willing to work. All wages in the platform are set and displayed to potential employers in US dollars.[8] Employers can post job listings, to which workers can apply, or alternatively search for workers that match their needs. Billing and payments are handled by the platform, and jobs are paid within two weeks of completion. The platform's revenues originate from fees charged to workers (in the form a percentage of their invoiced earnings) and clients (in the form of a percentage of all payments made to a worker).

We build our dataset by collecting data from the publicly-available profiles of workers in the platform. We focus our sample on 100,023 workers that have a completed profile and have positive earnings and job experience in the platform.[9] In addition to the worker's 'ask' hourly wage, the profiles contain the following information.

General information: The platform displays the name and location (country and city) of each worker.[10] It also reports the type of jobs or 'occupations' that each worker can perform, which are self-reported at the time the worker creates a profile and are selected from a predetermined list of 91 occupations. In addition, workers can specify their time availability, and provide a brief written description of their skills and interests in their profiles. We anonymize the dataset of all personal information and extract a worker's unique identifier along with their location, occupation, and time availability.

[8] All contracts are denominated in U.S. dollars. However, the platform offers clients the option to settle invoices denominated in U.S. dollars in the local currencies of several non-U.S. countries.

[9] Since creating a profile is easy and free of charge, a large fraction of profiles appear to be ghost accounts with no registered activity on the Platform. We exclude such inactive profiles from the analysis.

[10] The platform routinely sends freelancers and clients verification requests asking for documents that verify their residence (e.g., bank statements, credit card statements, and utility bills). The submitted address must match the location information that freelancers and clients entered on the Platform.

Skills: Workers can list several predetermined skills and take online examinations through the platform to certify their expertise in certain areas, such as 'English to Spanish Translation'. The platform offers more than 200 different tests. We observe the tests each worker takes, along with the scores and rank percentiles among the platform's population. We use the results from these tests as our primary measure of skills, as they are standardized across all workers.

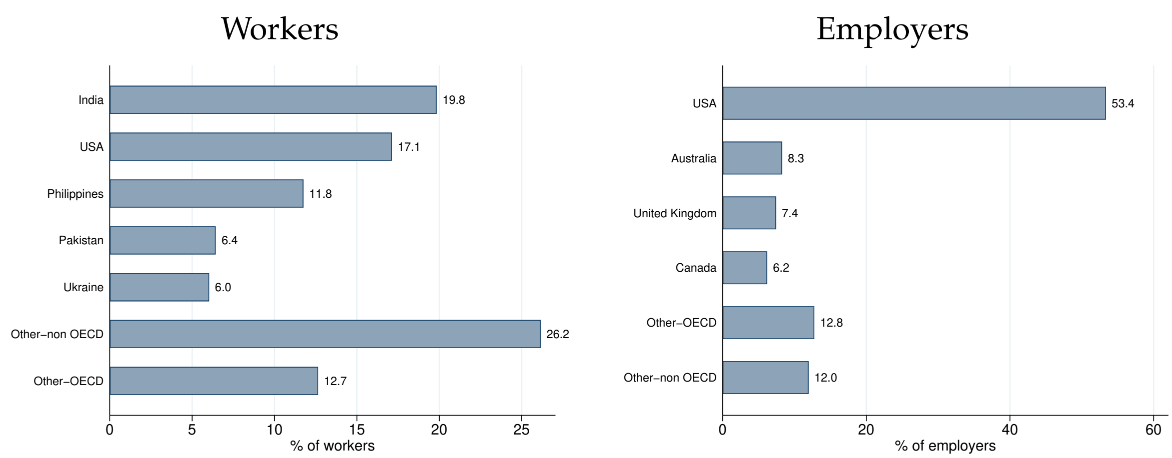
Experience and quality: In addition to the information provided by workers, the profiles record information that is based on the workers' interactions with the platform. Specifically, the platform records each worker's total earnings and total number of jobs completed. Additionally, it displays the average response time for each worker and the percentage of contracted jobs they have successfully finished, referred to as the 'success rate'. Finally, the Platform certifies experienced workers as 'Top-Rated.' To earn and maintain a Top Rated status, a worker must have, at a minimum, a completed profile, a job success rate of 90%, $1,000 in earnings in the previous year, and must have had some activity in the platform (i.e., accepted a job invitation or received earnings) in the past 90 days. Thus, the platform rewards its most active and successful workers by awarding them Top Rated status.

Job histories in the platform: For each job that a worker started, the platform reports a description of the job, the total payment and, if the contract was stipulated on an hourly basis, the transacted hourly rate and number of hours worked. It also reports the start date and, if the job is not still in progress, the end date of each job. Given the complexity of the process, we obtained a sample of the job histories for a subset of 30,520 workers. Finally, for a subsample of 348,000 of these jobs, we obtained information on the employer's identifier and location.

2.2 Summary statistics

The data collected include the profiles of more than 100,000 workers located across a total of 183 countries, although most workers are concentrated in a few countries. Overall, there are 26 countries with at least 500 workers, 65 countries with at least 100, and 90 countries with at least 50 workers. Figure 1 compares the geographical distribution of workers and employers in the data. Over 60% of the workers are concentrated in 5 countries: India, the US, Philippines, Pakistan, and Ukraine. Employers are even more concentrated—75% of employers are located in just 4 countries: the US (53.4%), Australia (8.3%), the UK (7.4%), and Canada (6.2%). While the US is a large source of both workers and employers, most employers (88%) are located in OECD countries, while most workers (70%) are located in non-OECD countries. This indicates that many workers from non-OECD countries work for employers in OECD countries. In fact, for 87% of the jobs in our sample, the worker and the employer are located in different countries.

Figure 1: Distribution of jobs across worker's and employer's locations

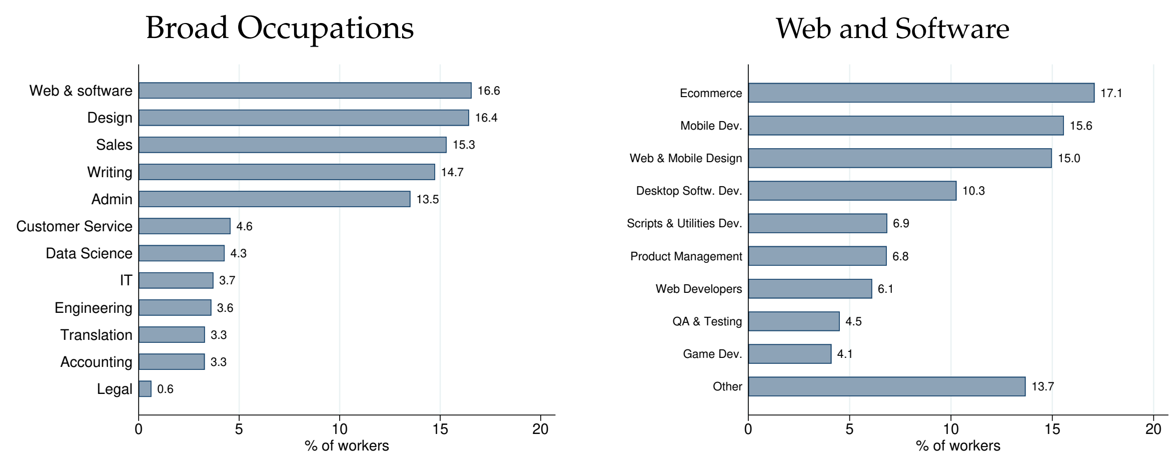


Notes: The figure shows the distribution of jobs across the workers' locations (left panel) and the employers' locations (right panel).

Figure 2 shows the distribution of workers across 12 broad occupations. In our sample, the largest occupations in terms of the number of workers are 'Web and Software', 'Design', and 'Sales', accounting for 16.6, 16.4, and 15.3 percent of the workers of our sample, respectively. In contrast, only 0.6 percent of the workers in our sample are listed in 'Legal'. Each broad occupation can be further disaggregated into detailed occupations. For example, the right panel of Figure 2 shows that within 'Web and software', 20 percent of workers are listed as 'E-commerce'. There are 91 detailed occupations in total, which we list in Appendix Table A1.

Table 1 reports summary statistics for some of the main variables that will be used in our analysis. Ask wages in the platform are high for international standards: the median and mean wages are 18 and 25 dollars, respectively. There is, however, a wide variation in wages: the gap between the 95th and 5th percentile of the wage distribution is 2.8 times as large as the mean. The average worker in the data has completed 69 jobs and earned 18,667 US dollars. The distribution of earnings exhibits large dispersion, with a 5th and 95th percentiles of 20 and 90,000 dollars, respectively. Although these numbers reflect cumulative earnings in the platforms, they are 6-9 times larger than the annual income

Figure 2: Workers by broad occupation



Notes: The left panel reports the share of the workers across the 12 broad occupations in the platform. The right panel reports the shares in each detailed occupation belonging to 'Web and Software'.

per capita in countries such as India, Pakistan, or the Philippines, and are also substantial in relation to the income per capita in the US. This suggests that a large number of workers are probably earning most of their income through the platform. Indeed, 42% of workers report being available more than 30 hours per week, and an additional 33% are available 'as needed'.

The platform allows workers to take standardized tests to signal their skills. The median (average) worker takes 3 (4) tests in the platform, and the standard deviation of (cross-test average) scores is 12% of the mean score. Finally, 41% of the workers in our sample are classified as 'Top Rated', and only 28% have a success rate of 100%.

Comparability of ask vs. transacted wages: As noted above, the dataset contains information on both the hourly 'ask' wage listed on the worker's profile and the hourly 'transacted' wage in each (hourly) job listed in the worker's job history. Figure A.1 in the Appendix shows a scatter plot of a worker's (log) ask wage in January 2019 and the workers' 2018-2019 average (log) hourly wage based on transactions recorded in their job histories. The figure shows that log transacted wages move close to one for one with log posted wages: The slope of the relationship is 0.91. The intercept in the relationship is -0.02, which means that on average, transacted wages are 2% lower than ask wages. Although this difference could naturally arise if, for example, employers bargain with workers before hiring them, the quantitative relevance of such mechanisms seem to be small.

Table 1: Summary statistics

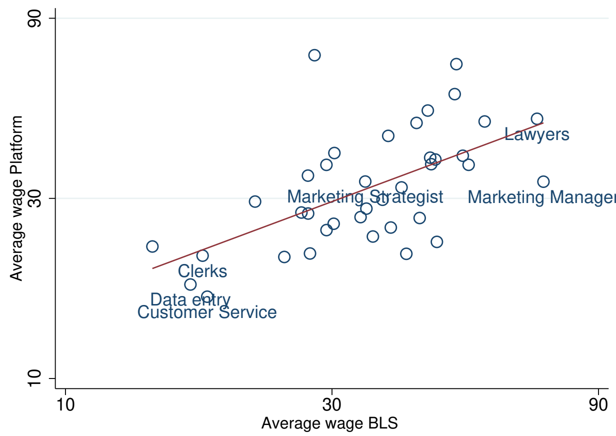
	Mean	Median	St. Dev.	5 pct	95 pct
Ask hourly wage	25	18	27	5	75
Number of jobs	69	10	642	1	147
Total earnings	18,667	4,000	62,558	20	90,000
Number of tests	4	3	4	1	10
Average score	4.23	4.25	0.50	3.38	5

	Share of workers	Success rate	Share of workers
Top Rated	0.41	N/A	0.42
Agency	0.15	<70%	0.02
		[70%,80%)	0.03
Available as needed	0.33	[80%,90%)	0.07
Available < 30 hs. per week	0.13	[90%,95%)	0.07
Available > 30 hs. per week	0.42	[95%,100%)	0.11
Availability N/A	0.12	100%	0.28

Notes: The top of the table reports moments of the distribution of worker characteristics. Hourly wage refers to the ask wage specified in the worker's profile. Number of jobs and total earnings refer to a worker's cumulative experience up to January 2019. Number of tests and average score refer to the standardized tests offered by the platform to workers to certify their skills. The bottom of the table reports the share of workers classified as 'Top Rated' by the platform, the share of workers that belong to an agency, the distribution of the time availability reported by workers and the distribution of success rates.

Remote vs. traditional wages for US workers across occupations: Finally, we compare remote to traditional wages for US workers in different occupations. We match the occupations in the platform to those in the Standard Occupational Classification (SOC) categories manually using the corresponding descriptions. Appendix Table A2 lists the concordance between the classifications. We obtain data on traditional wages by occupation for US workers from the U.S. Bureau of Labor Statistics (BLS). Figure 3 compares hourly wages in the platform to those provided by the BLS for 38 SOC occupations represented in our data. Remote wages are similar to traditional wages for US workers ranging between \$20 and \$80 per-hour depending on the occupation, though remote wages are more compressed than traditional wages. There is a strong positive relation between the two, suggesting that remote wages are in part shaped by what workers can earn in their local labor markers, an issue that we explore in detail in the following sections.

Figure 3: Remote vs. traditional wages for US workers



Notes: Each circle represents an occupation. The figure compares hourly average wages for US workers in the platform vs. wages in the BLS data for in different SOC occupations. The estimated slope is 0.55 (0.11) and the R-squared is 0.34.

3 Remote wages across locations

This section documents how remote wages vary across workers' and employers' locations. To do so, we estimate the following OLS regression using data on transacted wages:

$$w_{fi} = \mathbb{C}_i + \mathbb{D}_f + \mathbb{I}_{i=f} + \boldsymbol{\beta}' \boldsymbol{X_i} + \varepsilon_{fi}. \tag{1}$$

Here, w_{fi} denotes the (log) wage paid by employer f to worker i in a given job. $\mathbb{C}_i$ and $\mathbb{D}_f$ are full sets of fixed effects for the workers' and the employers' countries, respectively. The omitted country category is the US, so these fixed effects measure the average wage earned by workers and paid by employers in each country relative to the US. $\mathbb{I}_{i=f}$ is an indicator variable that is equal to one if the employer and worker are in the same country. $\boldsymbol{X_i}$ is a vector of worker characteristics, containing experience variables (log earnings and number of jobs), skill variables (number of tests and the average score), quality ratings (whether the worker is Top Rated, and dummies for success rates), availability variables (dummies for full/part-time, and dummies for response time), dummies for the occupations listed in the worker's profile, and an indicator for whether the worker works in an agency (multi-worker or single worker).

A variance decomposition of equation (1) shows that the workers' locations account for 31% of the dispersion of wages, which is more than the variance accounted for by all other controls (this decomposition splits the contribution of the covariance terms equally across regressors). In contrast, employers' locations account for only 0.04% of the variance in wages, in part because employers are located in a few countries.[11]

Figure 4a plots average wages across workers in each country relative to the US, obtained from the fixed effects $\mathbb{C}_i$ in equation (1), and the relative GDP per capita in each country with at least 100 workers with transacted wage data. There is a very strong and positive relationship between workers' remote wages and the GDP per capita in their country. The slope of this relationship is 0.22 (SE 0.03) and the R-squared is 0.58. These cross-country differences in average wages are not driven by observable worker characteristics nor by differences in the location of the employers. Appendix Figure A.2 shows similar results using the larger sample of workers with available ask wage data, and Appendix Figure A.3a shows a similar relationship between non-residualized wages and GDP per capita. Note that while cross-country differences in remote wages are pervasive, they are about one-fifth the size of the differences in GDP per capita.

Figure 4: Wages and GDP per capita relative to the US

(a) Average wage across workers (b) Average wage across employers

Notes: The x-axes report the (log of) the relative GDP per capita in US dollars, taken from the World Development Indicators (WDI). Panel (a) and panel (b) plot $\mathbb{C}_i$ and $\mathbb{D}_f$ relative to the US obtained from the country fixed effects estimated in equation (1). The red lines show the linear fit of the data. The estimated slope is 0.22 (0.03) in panel (a) and 0.07 (0.02) in panel (b), and the R-squared are 0.58 and 0.40, respectively.

Figure 4b plots the average wages across employers in each country relative to the US, obtained from the fixed effects $\mathbb{D}_f$ in equation (1), for countries with at least 100 employers.

[11] Appendix Table A3 reports the results of the estimation in equation (1), and Appendix Table A4 reports the full variance decomposition. A regression of log-wages on the set of country fixed effects $\mathbb{C}_i$ has an R^2 of 0.41, while the R^2 of estimating equation (1) with all the additional controls is 59%.

The figure shows a very weak relation between the remote wages paid by the employers and the level of GDP per capita in their country. This relationship is driven by a few outliers; only employers from Pakistan, India, and the Philippines appear to pay relatively lower wages than those in the US.

Wage differences across US states: We now document differences in remote wages across workers located in different US states. We follow the strategy in the previous analysis and compare average wages in each state after residualizing them for worker characteristics. Unfortunately, we do not observe the transacted wage for enough workers and employers in each of the US states to estimate (1) at the state level (there are only 12 states with more than 100 workers that report these data). Thus, we use data on ask wages for workers located in the US to estimate:

$$w_i = \mathbb{S}_i + \boldsymbol{\beta}'\boldsymbol{X_i} + \varepsilon_i. \tag{2}$$

Here, w_i is the ask wage of worker i, and $\mathbb{S}_i$ is the full set of fixed effects for the workers' state. The omitted state is California—the state with the most workers in our sample—so the state fixed effects measure average wages in each state relative to the average wage earned in California. Since equation (2) is estimated on the ask wage data, we cannot control for the location of the employer (workers only post one ask wage in their profiles).

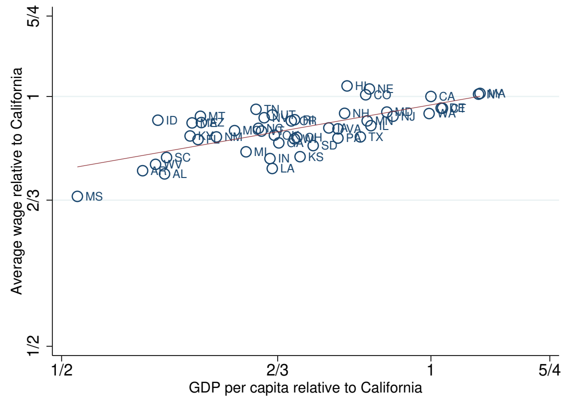
Figure 5 compares relative wages to the relative GDP per capita of each of the 47 states with at least 30 workers in our sample.[12] It shows that the pattern across US states is similar to the one we observe across countries: Workers from richer states earn on average higher wages. The slope of this relation is 0.26 (SE 0.04) and the R-squared is 0.48. These patterns are remarkably similar to the cross-country patterns documented above.[13]

Wage differences across remote workers located in different countries and US states suggest that the worker's location plays a large role in shaping wages, even in remote jobs that do not require the worker to be present at a specific location. Below, we empirically evaluate some potential explanations for this phenomenon.

[12]We exclude North Dakota, Wyoming, and Alaska since they only have 18, 25, and 26 workers, respectively in our sample.

[13]Non-residualized wages in each state are reported in Appendix Figure A.3b.

Figure 5: Wages and GDP per capita across US states (ask wages)



Notes: The x-axis reports the (log of) the relative GDP per capita in US dollars, taken from the Bureau of Economic Analysis. The figure plots the average ask wage in each state relative to California, obtained from state fixed effects in equation (2). The red line shows the linear fit of the data. The estimated slope is 0.26 (0.04) and the R^2 is 0.48.

3.1 Disentangling sources of cross-country wage differences

Trade costs: One potential reason for wages to vary with the worker's location is that employers may find it more costly to work with workers from distant countries. With this in mind, Appendix Figures A.4a and A.4b plot average wages across workers' and employers' locations obtained from a version of (1) that incorporates controls for the time difference and geographical distance between the employer's and the worker's countries, and for whether the countries share a common language, currency, and legal origin. The figure shows that these controls do not affect the main results in Figures 4a and 4b.

Comparison with non-remote wages and local prices: Differences in GDP per capita may not be representative of the cross-country differences in non-remote wages for the type of occupations that are traded in the platform. With this in mind, we obtain data on non-remote wages for occupations that are similar to those represented in the platform from the International Comparison Program (ICP) from the World Bank.[14] Appendix Figure A.5a shows that the relation between remote wages and non-remote wages from similar occupations resemble that in Figure 4a. Appendix Figure A.5b compares remote wages to local price levels, and shows that remote wages are higher for workers living in more expensive countries.

[14] We include the following occupations included in the ICP database: Accounting and Bookkeeping Clerks, HR Professionals, Computer Operators, Data Processing Managers, and Database Administrators.

Controlling for employer fixed effects: The wage gaps we observe could potentially be driven by differences in the employers that hire workers in different countries. Figure 4a plots the dummies $\mathbb{C}_i$ in equation (1), which also controls for the country of employer fixed-effects $\mathbb{D}_f$. We can also estimate an analogous equation that uses unique employer identifiers to control for employer fixed-effects. We estimate this regression using the sample of employers for which we observe more than one worker, which accounts for 42% of the observations (unfortunately, we do not observe all the workers hired by each employer). Appendix Figure A.6a plots the average wage in each location residualized with employer fixed-effects. The figure continues to show a strong relationship between the (residual) remote wages and the GDP per capita of the location of the workers, although the slope of this relation drops to 0.15 (SE 0.02). This shows that even when working for the same employer, remote workers from richer countries earn higher wages.

Controlling for worker fixed effects: Finally, we evaluate whether workers price to market, that is, whether the wage earned by a particular worker depends on the employer's location. With this in mind, we can estimate a version of (1) that includes worker fixed effects instead of all the worker-level controls. Appendix Figure A.6b plots the wages paid by employers from each country, obtained from the dummies $\mathbb{D}_f$ in this regression, for the set of countries that have more than 100 workers. Workers get paid somewhat more when working for employers from richer countries, although the relation is mild and driven by a only few countries (slope of 0.05 with a standard error of 0.02).

The results from this section show that remote wages are strongly correlated with the GDP per capita in the worker's locations. This finding is not accounted for by any observable differences in workers', jobs, or employer characteristics, though it may be in part driven by unobserved differences in worker characteristics. The following section uses data on wage changes to further understand this relationship and to study how remote wages respond to international shocks.

4 Remote wages and international shocks

This section first proposes a model of a remote labor market where remote wages can differ across locations due to differences in workers' characteristics (productivities) or differences in local conditions. It then uses the model and data on wage changes to disentangle these two alternatives and to study how remote wages respond to international shocks.

4.1 Conceptual framework

Remote labor demand: We consider a market for remote labor populated by a continuum of workers who live in different locations indexed by c and work in different sectors indexed by j. The market is competitive: a representative firm hires workers from different locations and sectors to produce a final good, taking wages as given. The production function for the final good is:

$$Y_t = \left[\sum_j \left[Y_t^j \right]^{\frac{\eta-1}{\eta}} \right]^{\frac{\eta}{\eta-1}}, \tag{3}$$

where Y_t^j denotes output from sector j. Cost minimization implies

$$Y_t^j = \left[\frac{\Omega_t^j}{P_t} \right]^{-\eta} Y_t, \tag{4}$$

where Ω_t^j and P_t are prices of the sectorial and final output. The sectorial output is produced according to

$$Y_t^j = \left[\sum_c \left[A_{ct}^j L_{ct}^j \right]^{\frac{\rho-1}{\rho}} \right]^{\frac{\rho}{\rho-1}}. \tag{5}$$

Here, L_{ct}^j denotes the efficiency units of labor from location c in sector j, A_{ct}^j is a factor-augmenting technology term that acts as a demand shifter, and ρ is the elasticity of substitution across workers from different locations. Equation (5) assumes that efficiency units of labor from the same location are perfect substitutes. On the other hand, units from different locations can be imperfect substitutes if $\rho < \infty$. An alternative to assuming that workers from different locations are imperfect substitutes is to assume that they specialize in different tasks that are necessary to produce the sectorial good. Appendix A.4 derives such an alternative model and shows that it is isomorphic to the one presented here.

Let Ω_{ct}^j denote the dollar remote wage per efficiency unit of labor from location c in sector

j. Cost minimization implies that the demand for labor is given by

$$L_{ct}^{j} = \left[A_{ct}^{j}\right]^{\rho-1} \left[\frac{\Omega_{ct}^{j}}{\Omega_{t}^{j}}\right]^{-\rho} Y_{t}^{j}, \tag{6}$$

and that the unit cost of production in sector j is

$$\Omega_{t}^{j} = \left[\sum_{c} \left[\Omega_{ct}^{j}/A_{ct}^{j}\right]^{1-\rho}\right]^{\frac{1}{1-\rho}}. \tag{7}$$

Remote labor supply: Each location is inhabited by a continuum of workers indexed by i, each of which specializes in one sector j. Each worker is endowed with Z_{it}^{j} efficiency units of labor in one of the sectors, and can work in the remote or in the local labor market. In the local labor market, workers earn a wage given by $Z_{it}^{j} \times B_{ct}^{j}/H_{i}^{j}$, where B_{ct}^{j} is the wage per efficiency unit of labor in the local labor market denominated in dollars, and H_{i}^{j} is a worker-specific cost for working in the local labor market, which can be interpreted as the fraction of time that a worker must spend commuting.[15] We assume that B_{ct}^{j} is exogenously determined.[16] A worker chooses to work remotely if and only if the wage for remote labor exceeds the wage paid in the local labor market. Thus, there exists a cutoff

$$H_{i}^{j} \geq \underline{H}_{ct}^{j} \equiv B_{ct}^{j}/\Omega_{ct}^{j}, \tag{8}$$

such that workers with H_{i}^{j} above this cutoff choose to work remotely. We assume that Z_{it}^{j} and H_{i}^{j} are independently distributed and that the c.d.f. of H is $G(H) = 1 - \left[\frac{\kappa_{c}^{j}}{H}\right]^{\theta}$ with support $[\kappa_{c}^{j}, \infty)$. Let N_{ct}^{j} denote the number of workers in location c. Then, the supply of remote labor in sector j from location c is given by

$$L_{ct}^{j} = N_{ct}^{j} \times Z_{ct}^{j} \times \left[1 - G(\underline{H}_{ct}^{j})\right] = \tilde{N}_{ct}^{j} \left[\frac{\Omega_{ct}^{j}}{B_{ct}^{j}}\right]^{\theta}, \tag{9}$$

[15]More generally, $1/H_{i}^{j}$ is the relative cost of working in the remote vs. in the local labor market. H_{i}^{j} could be smaller than one, in which case workers perceive working in the local labor market as advantageous, other things equal.

[16]We make this simplifying assumption since our interest is on how local wages affect remote wages, and, while rapidly growing, remote labor markets are still small relatively to local labor markets.

where $Z^j_{ct} \equiv \mathbb{E}_c\left[Z^j_{it}\right]$ denotes the average efficiency units of labor across all workers from location c in sector j, and $\tilde{N}^j_{ct} \equiv N^j_{ct} Z^j_{ct}\left[\kappa^j_c\right]^\theta$ collects supply shifters other than B^j_{ct}. Equation (9) states that the labor supply elasticity is given by θ.

Equilibrium: Combining equations (6) and (9) with (4), and using lowercase to denote variables in logs ($\omega^j_{ct} \equiv ln\Omega^j_{ct}$, and $\omega^j_t = ln\Omega^j_t$), we obtain the equilibrium wage per efficiency unit of remote labor for sector j in location c:

$$\omega^j_{ct} = \frac{\theta}{\rho+\theta} b^j_{ct} + \frac{\rho-\eta}{\rho+\theta}\omega^j_t + \frac{1}{\rho+\theta}\varphi^j_{ct}, \tag{10}$$

$$\tag{11}$$

$$var_c\left[\omega^j_{ct}\right] = \left[\frac{\theta}{\rho+\theta}\right] var[b^j_{ct}] + \frac{1}{\rho+\theta} var\left[\left[\rho-1\right]a^j_{ct} - \tilde{n}^j_{ct}\right] \tag{12}$$

where $\varphi^j_{ct} \equiv [\rho-1]\, a^j_{ct} - \tilde{n}^j_{ct} + \eta p_t + y_t$ collects aggregate and location-sector-specific supply and demand shifters.

Remote wages and workers' locations: We now evaluate wage differences across remote workers. Let $w^j_{it} \equiv \omega^j_{ct} + z^j_{it}$ denote the log wage per unit of time of remote worker i in location c and sector j (i.e., the equivalent of hourly wages in the platform). Then,

$$w^j_{it} = \frac{\theta}{\rho+\theta} b^j_{ct} + \frac{\rho-\eta}{\rho+\theta}\omega^j_t + \frac{1}{\rho+\theta}\varphi^j_{ct} + z^j_{it}. \tag{13}$$

Equation (13) states that wage differences across workers in the same sector can arise from differences in local wages, b^j_{ct}, location-specific demand and supply shifters, φ^j_{ct}, and workers' efficiency units, z^j_{it}.[17] Note that if workers from different locations are perfect substitutes, $\rho \to \infty$, demand is perfectly elastic and wage differences arise only due to differences in z^j_{it}. If, instead, labor supply is close to being perfectly elastic, $\theta \to \infty$, wage differences are given by differences in local wages b^j_{ct} and differences in z^j_{it}. For finite values of ρ and θ, the elasticity of remote wages with respect to local wages is positive but less than one, $\frac{\theta}{\rho+\theta} < 1$. Equation (13) underscores that, while our model is highly stylized, remote wages will be tied to local labor market conditions insofar as both: (i) the labor demand from individual locations is downward sloping; and (ii) the labor supply from those locations is upward sloping (see Enrico 2011 and Card et al. 2018 for a discussion of

[17] Note that if local wages b^j_{ct} are correlated with local prices, the model also predicts that remote wages should be higher in more expensive locations.

similar determinants of wage differences in the context of domestic local labor markets). Appendix A.4 provides alternative micro-foundations for such conditions.

We can use equation (13) to interpret the results from Section 3. If local wages can be proxied by the GDP per capita in a location, equation (13) suggests that the partial elasticity of wages with respect to GDP per capita is $\frac{\theta}{\rho+\theta}$. If the unobserved supply and demand shifters and productivities in equation (13) (φ_c, and Z_c) are uncorrelated with GDP per capita, then the evidence from Section 3 suggests that $\frac{\theta}{\rho+\theta} \simeq 0.2$. This orthogonality condition can be violated if, for example, workers in richer countries have more efficient units z^j_{it}, and differences in z^j_{it} are not fully captured in the controls in equation (2). The following section uses time variation in wages to distinguish these alternative interpretations.

Wage changes: We now evaluate the model's predictions for wage changes. We denote the change in a variable x_t by dx_t. Since we do not observe changes in local wages at short frequencies, we write the change in local wages expressed in dollars as

$$db^j_{ct} = \gamma^j_{ct} + \pi_{ct} + de_{ct}, \tag{14}$$

where γ^j_{ct} is the growth of local wages in constant local currency units, π_{ct} is the inflation rate, and de_{ct} is the change in the exchange rate denominated in dollars per unit of local currency.[18]

Let $dx^j_t \equiv \sum s^j_{ct} dx_{ct}$ denote the (sector-specific) cross-country average change in a variable, with weights s^j_{ct} corresponding to a country's cost share in a sector. Differentiating equations (7) and (13) and substituting yields:

$$dw^j_{it} = \frac{\theta}{\rho+\theta}\left[de_{ct} + \pi_{ct}\right] + \frac{\rho-\eta}{\rho+\theta} dw^j_t + d\psi^j_{ct} + dz^j_{it}, \tag{15}$$

with

$$dw^j_t = \frac{\theta}{\theta+\eta}\left[de^j_t + \pi^j_t\right] + d\phi^j_t. \tag{16}$$

Here, $dw^j_t \equiv \sum_c s^j_{ct} \mathbb{E}_c \left[dw^j_{it}\right]$ is an index of wage changes in the remote market, while $d\psi^j_{ct}$ and $d\phi^j_t$ collect supply and demand shifters (See Appendix A.3 for a derivation.).

[18] Equation (14) states that, to obtain the (log) change in local wages expressed in dollars, we add the inflation and the change in the exchange rate to the change in real wages. Since we do not have data on local wage inflation at short frequencies, we approximate it with price inflation in the next section.

Equations (15) and (16) state that the partial exchange rate pass-through elasticity is $\frac{\theta}{\rho+\theta}$, and that wages respond to average wages in the remote market with an elasticity of $\frac{\rho-\eta}{\rho+\theta}$.

4.2 Estimation

This section uses data on the workers' job histories to estimate how wages respond to international shocks.

4.2.1 Preliminaries

The job histories cover a sample of 641,679 jobs performed between January 2012 and January 2020. As noted in Section 2, for each job in the data, we observe the start date, the total payment, the worker's identifier and country, and a job description. For 85,095 jobs, we also observe the sector to which the job was assigned in the platform. We aggregate these sectors into four broad sectors: 'Admin and Sales,' 'Design,' 'Web and Programing,' and 'Writing.' We then assign sectors to the remaining jobs using the information from the job descriptions using a machine-learning algorithm.[19]

We restrict our analysis to jobs that were billed on an hourly basis, and thus an hourly wage is observable (along with the number of hours worked).[20] The start date of the job is reported at a monthly frequency, though a worker can start multiple jobs in the same month. We collapse the data at the monthly level so that the unit of observation is a worker-sector-month. After taking the difference between two consecutive jobs, this leaves a sample of 88,399 wage changes.

Finally, not all workers are observed each month-sector, both because workers may not start new jobs in a sector in a particular month, and because our data only contains a subset of the jobs in the platform. With this caveat in mind, we denote by $\Delta_s w_{it}^j \equiv w_{it}^j - w_{it-s}^j$ the log-change in the wage of a worker in sector j that is observed in months t and $t-s$ (and not in between). More generally, we denote the s-period change in a variable by $\Delta_s x_t \equiv x_t - x_{t-s}$, and refer to the period itself as time-spell t_s. We summarize the distribution of wage changes in Appendix Table A5. In the following analysis, we use

[19] The algorithm assigns a probability that a job belongs to each sector based on keywords from the job descriptions. For example, a job with the description 'looking for a grant writer' will likely be assigned to the sector 'writing' based on the keyword 'writer.' We detail the algorithm in Appendix A.2.

[20] About 50% of the jobs in the job-level dataset are billed as a 'fixed price' job, in which workers charge a predetermined price for completing a job. For these jobs, we observe how much workers are paid but not how many hours they work. We exclude these jobs from the analysis in this section.

data on monthly exchange rate changes and CPI inflation obtained from the International Financial Statistics.

4.2.2 Estimating partial exchange rate pass-through elasticities

We start by describing how to estimate partial pass-through elasticities from equation (15). Note that $\Delta_s w_t^j$ varies across time spells and sectors, so that we can estimate the equation as:

$$\Delta_s w_{it}^j = \beta_1 \Delta_s e_{ct} + \beta_2 \pi_{ct_s} + \mathbb{C} \times \mathbb{J} \times s + \mathbb{T}_{t_s}^j + \epsilon_{it_s}^j. \tag{17}$$

Here, $\mathbb{C} \times \mathbb{J} \times s$ is the product between country fixed effects, sector fixed effects, and the duration s of the time-spell, which controls for the country-sector-specific linear trends in the demand and supply shifters ψ_{ct}^j. $\mathbb{T}_{t_s}^j$ is a set of fixed effects for each period by spell-duration by sector combination ($t \times s \times j$) which control for the aggregate and sector-specific shifters in ψ_{ct}^j. The error term is given by $\epsilon_{it_s}^j \equiv \Delta_s \tilde{z}_{it}^j + \Delta_s d\tilde{\psi}_{ct}^j$, where the notation $\tilde{x}$ denotes the deviation of a variable from the sector-time-spell average and its country trend. Equation (17) is similar to the medium-run exchange rate pass-through regressions estimated by Gopinath et al. (2010). The coefficients β_1 and β_2 are identified from both time and country variation in exchange rates and inflation.

Estimating (17) by OLS yields consistent estimates of β_1 if the error term ϵ_{ijt_s} is orthogonal to changes in exchange rates and inflation across countries, i.e. $cov(\Delta_s \tilde{z}_{it}^j + \Delta_s \tilde{\psi}_{ct}^j, \Delta_s e_{ct}) = 0$. This exclusion restriction requires changes in exchange rates to be uncorrelated to trend deviations in sectoral productivity and supply and demand shifters at monthly frequencies. An extensive literature on the 'exchange rate disconnect' shows empirically that this restriction holds at short frequencies.[21] Finally, we note that we will test the restriction imposed by the model $\beta_1 = \beta_2$ empirically rather than imposing it in our estimation.

4.2.3 Estimating the effect of competitors' wages

According to equation (15), wages respond to changes in competitors' wages with an elasticity of $\frac{\rho-\eta}{\rho+\theta}$. We cannot test this implication using equation (17), since $\Delta_s w_t^j$ is absorbed

[21] See, e.g., Itskhoki and Mukhin (2017).

by the fixed-effects $\mathbb{T}^j_{t_s}$. We thus estimate the following equation:

$$\Delta_s w^j_{it} = \beta_1 \Delta_s e_{ct} + \beta_2 \pi_{ct_s} + \beta_3 \Delta_s w^j_t + \mathbb{C} \times \mathbb{J} \times s + \mathbb{T}_{t_s} + \varepsilon^j_{it_s}, \tag{18}$$

where $\varepsilon^j_{it_s} \equiv \Delta_s \hat{z}^j_{it} + \Delta_s \hat{\psi}^j_{ct}$, and $\hat{x}$ denotes the deviation of a variable from the time-spell average and the country-sector trend. Here, $\mathbb{T}_{t_s}$ denotes a set of fixed effects of each period by spell-duration combination ($t \times s$). To implement equation (18), we need to construct an index of average wage changes in each sector, $\Delta_s w^j_t \equiv \sum_c s^j_{ct} \mathbb{E}_c \left[\Delta_s w^j_{it}\right]$. Obtaining such an index is not straightforward since, as mentioned above, the set of workers observed in our data changes from period to period. Thus, for any given time spell t_s, data on $\Delta_s w^j_{it}$ is not observed for many workers.

With this in mind, we approximate $\Delta_s w^j_t$ as the change in the average of wages observed in periods $t - s$ and t, after controlling for the composition of workers over time. More specifically, we estimate

$$w^j_{it} = \delta^j_i + \delta^j_t + v^j_{it},$$

where δ^j_i and δ^j_t are two sets of worker-sector and time-sector fixed-effects, respectively. We construct a series of the wage index as the series of the estimated time fixed effects, i.e., $\Delta_s w^j_t = \Delta_s \delta^j_t$.[22]

Finally, the OLS estimates of (18) are inconsistent if $\Delta_s w^j_t$ is correlated with $\varepsilon^j_{it_s}$, which would be the case if the detrended aggregate shifters $\Delta_s \hat{\phi}^j_t$ and $\Delta_s \hat{\psi}^j_{ct}$ are correlated. We thus pursue an IV approach. From equation (16), a natural instrument for $\Delta_s w^j_t$ is

$$\Delta_s \Theta^j_t \equiv \pi^j_{t_s} + \Delta_s e^j_t, \tag{19}$$

which correlates with $\Delta_s w^j_t$ but is orthogonal to $\varepsilon^j_{it_s}$ under the exclusion restriction. In building the instrument in (19), we proxy s^j_{ct} by the share of jobs performed by workers from country c in sector j throughout our sample. Figure A.7 in the Appendix reports that there is substantial variation in s^j_{ct} across sectors.

[22] This procedure recovers up to a first-order approximation the time series of dw^j_t. To see this, note that from equations (15) and (16) we have:

$$\begin{aligned} d\delta^j_t &= \frac{\theta}{\rho+\theta}\left[de_t + \pi_t\right] + \frac{1}{\rho+\theta}\left[d\varphi^j_t + \theta\gamma^j_t\right] + \frac{\theta+\eta}{\rho+\theta} dz^j_t + \frac{\rho-\eta}{\rho+\theta}\frac{1}{1-\rho} da^j_t + \frac{\rho-\eta}{\rho+\theta} dw^j_t \\ &= \frac{\theta+\eta}{\rho+\theta} dw^j_t + \frac{\rho-\eta}{\rho+\theta} dw^j_t = dw^j_t. \end{aligned}$$

4.2.4 Results

We present our estimates in Table 2. Column 1 shows the results from estimating equation (17) by OLS, which in addition to $\Delta_s e_{ct}$ and π_{ct_s} includes country-sector-specific trends and sector-time-spell fixed effects. We cluster standard errors at the sector-time-spell and country level. The estimated partial pass-through elasticity is $\hat{\beta}_1 = 0.203$ and is estimated to be statistically different from zero. This indicates that while dollar wages respond to changes in the dollar exchange rate, the corresponding elasticity is low. This, in turn, shows that wages in local currency move in tandem with the dollar exchange rate (with an elasticity of 0.797). The coefficient on inflation is similar, $\hat{\beta}_2 = 0.227$, though we cannot reject the null hypothesis that it is equal to zero at a 1% significance level. In addition, we cannot reject the null hypothesis that $\beta_1 = \beta_2$. Under the assumption that changes in exchange rates affect local wages denominated in dollars but are uncorrelated to changes in the workers' productivity, this result suggests that remote wages are tied to the conditions that workers face in their local labor markets.

Column 2 shows the results from estimating equation (18) by OLS, which controls for country-sector-specific linear trends and time-spell fixed effects but includes $\Delta_s w_t^j$ instead of the sector-time-spell fixed effects $\mathbb{T}_{t_s}^j$. Standard errors are clustered at the sector-time-spell and country level. The coefficients on the dollar exchange rate and inflation are very close to those in Column 1 and given by $\hat{\beta}_1 = 0.212$ and $\hat{\beta}_2 = 0.197$, respectively. The coefficient on the aggregate wage index is $\hat{\beta}_3 = 0.781$ and is statistically different from zero.

Column 3 reports the 2SLS estimates in which we use $\pi_{t_s}^j$ and $\Delta_s e_t^j$ separately as instruments for $\Delta_s w_t^j$. The estimated coefficient on the exchange rates and inflation are almost identical to those in Column 2. More importantly, the coefficient on $\Delta_s w_t^j$ is 0.741, and is statistically significant at the 1% level. The bottom of Table 2 reports the F-statistic of the first stage, which is well above conventional critical values. Appendix Table A6 reports the first-stage regression in Column 1 and shows that the coefficients on $\pi_{t_s}^j$ and $\Delta_s e_t^j$ are statistically significant and contribute to the variation in $\Delta_s w_t^j$. These results show that dollar wages do respond to changes in competitors' wages driven by changes in foreign inflation and exchange rates. In particular, the estimates imply that a 1% increase in the wages in country $c' \neq c$ increases wages in country c by $0.741 \times \left[s_{c'}^j \times 1\%\right]$.[23]

[23] Table A7 in the Appendix reports the results obtained after imposing the constraint $\beta_1 = \beta_2$.

Table 2: Wage changes and international shocks

	(1)	(2)	(3)
	$\Delta_s w_{ijt}$	$\Delta_s w_{ijt}$	$\Delta_s w_{ijt}$
$\Delta_s e_{ct}$	0.203***	0.212***	0.213***
	(0.058)	(0.052)	(0.053)
π_{c,t_s}	0.227*	0.197*	0.196*
	(0.120)	(0.103)	(0.103)
$\Delta_s w_{jt}$		0.781***	0.741***
		(0.073)	(0.252)
Observations	88399	88399	88399
Test $\beta_1 = \beta_2$	0.84	0.87	0.85
Specification	OLS	OLS	2SLS
F stat 1st stage			39.8

Notes: Column (1) reports the OLS estimates from equation (17), which contains period by spell-duration by sector fixed effects. Columns (2) and (3) report the OLS and 2SLS estimates from equation (18) respectively, and include period-by-spell-duration fixed effects. All columns include country by sector by spell-duration fixed-effects. The nominal exchange rate e_{ct} is measured in US$ per unit of local currency. Standard errors are clustered at the sector-time-spell and country level*: significant at the 10% level, **: significant at the 5% level, *** significant at the 1% level.

4.3 Robustness

This section presents several robustness exercises that complement the results presented above.

Conditioning on a wage change: The conceptual framework in Section 4.1 assumes that workers' wages are flexible, which is a good approximation in the context of cross-country wage comparisons in Section 3. However, if wages are sticky in the short run, our time series estimates can be biased toward zero. In fact, Appendix Table A5 shows that wages do not change between subsequent jobs in around 25% of our observations.

To address this concern, we reproduce our regression analysis using the subsample of jobs for which we observe a non-zero wage change. Column 3 in Appendix Table A7 reports the results. The coefficient on the change in the domestic exchange rate increases from the baseline value of 0.213 to 0.251, and the coefficient in domestic inflation increases from 0.196 to 0.240. Overall, the analysis of non-zero wage changes reveals that wages are indeed more responsive. However, the quantitative differences relative to our baseline analysis are small.

Alternative measures of competitors' wages: A potential source of concern is that the aggregate wage index $\Delta_s w_t^j$ is, by definition, a function of each worker's wage and is thus correlated with the error term in equation (15). In the model of Section 4.1, there is a continuum of workers, so this dependence vanishes. To further reduce concerns about the endogeneity of our regressor, we reestimate equation (15) using the leave-one-out index for the competitors' wages, $\Delta_s w_{-it}^j \equiv \sum_{l \neq i} \frac{s_{lt}^j}{1-s_{it}^j} \Delta_s w_{lt}^j = \left[\Delta_s w_t^j - s_{it}^j \Delta_s w_{it}^j\right] / \left[1 - s_{it}^j\right]$, where s_{it}^j is the market share of worker i in sector j.[24] Note also that if all workers have small market shares $s_{it}^j \to 0$ (as they do in practice), then $\Delta_s w_{-it}^j \to \Delta_s w_t^j$. The results of this alternative estimation are presented in Column 4 of Appendix Table A7, and coincide with our baseline estimation.

Placebo analysis: In our baseline estimates, we classified jobs into four broad sectors using the jobs' descriptions and a machine-learning algorithm, and assumed that a worker's wage depends on the wages of other workers in the same sector. To validate this approach, we conduct a placebo analysis in which we evaluate if workers respond to changes in the wages of remote workers from other sectors. We would expect workers to respond more strongly to competitors in their sector than to remote workers from different sectors. With this in mind, we match each job to its 'most distant' sector in the following way. For each job, the algorithm estimates the likelihood that the job belongs to each of the four broad sectors. In our baseline analysis, we assigned each job to the sector with the highest estimated likelihood. For this placebo analysis, we also assign a 'most distant' to each job, which is given by the sector with the lowest estimated likelihood. We then extend the estimating equation (18) to include the average wage change in the job's most distant sector as an additional regressor.

Column 5 of Table A7 in the Appendix reports the results. The inclusion of this additional wage change barely affects the coefficient on the competitors' wages. In contrast, the co-

[24] Note that equation (15) can also be written as

$$dw_{it}^j = \frac{\theta}{\tilde{\rho}_{it} + \theta + s_{it}^j \eta} \left[de_{ct} + \pi_{ct}\right] + \frac{\tilde{\rho}_{it}^j - \eta \left[1 - s_{it}^j\right]}{\tilde{\rho}_{it}^j + \theta + s_{it}^j \eta} dw_{-it}^j + \frac{d\psi_{ct}^j + dz_{it}^j}{\tilde{\rho}_{it}^j + \theta + s_{it}^j \eta}, \tag{20}$$

where $\tilde{\rho}_{it}^j \equiv \rho \left[1 - s_{it}^j\right]$ and $dw_{-it} \equiv \sum_{l \neq i} \frac{s_{lt}}{1-s_{it}} dw_{lt}$. Note that if all workers have small market shares, $s_{it}^j \to 0$, then $\tilde{\rho}_{it}^j \to \rho$.

efficient on the wage changes of the most distant competitors is much smaller in absolute value and is not statistically different from zero, as expected.

Alternative assumptions on country-trends: Columns 6 and 7 in Appendix Table A7 re-estimate equations (17) and (18) using alternative controls for the country-specific trends. Column 6 does not control for country-sector-specific trends. Column 7 does not control for time-spell fixed effects. The table shows that our results are robust to the different ways we control for country-specific trends.

Estimation on the worker-level data: Finally, we reestimate partial ERPT elasticities using data on ask wages. As detailed in Section 2, these data are in a more conventional format as the wage posted by each worker is observed twice, once in January 2019 and once in November 2020. Workers are listed across (possibly more than one of) the 91 occupations in the platform described in Table A1 in the Appendix. The regression sample contains 226,569 pairs of worker-sector observations corresponding to 60,840 workers who have posted wages in both periods. We can estimate the partial pass-through elasticities from equation

$$\Delta w_i^j = b_1 \Delta e_c + b_2 \pi_c + \mathbb{S}^j + \mu_i^j, \tag{21}$$

where Δx represents the change in a variable between the two periods, and $\mathbb{S}^j$ is a vector of sector fixed effects. We omitted time subscripts to highlight that we only observe one wage change per-worker. Here, the coefficients are identified from the country variation in exchange rates and inflation. An important difference with equation (17) is that, since exchange rates only vary at the country level, we cannot include country fixed effects to control for country-specific trends. Nonetheless, b_1 can be consistently estimated by OLS if changes in exchange rates are orthogonal to sector-specific supply and demand shocks.

We report our results in Column 8 of Appendix Table A7. We cluster standard errors at the country level. The estimated pass-through coefficient is 0.084, and the coefficient for inflation is 0.095. The coefficients are smaller than those estimated with the job data, reinforcing our conclusion that there is low pass-through into dollar wages. This occurs in part because ask wages are more sticky than transacted wages, and a large fraction of ask wages that do not change during our period. As in the previous section, we cannot reject the null hypothesis that $\beta_1 = \beta_2$.

5 Which remote jobs are more frequently offshored?

This section documents how frequently are jobs offshored in different occupations. While existing measures of job offshorability typically hinge on subjective judgments of how to classify the different attributes of a job (Blinder and Krueger 2013), we measure which jobs are actually offshored using data on the prevalence of cross-border contracts in an occupation.

5.1 Measurement

We define a job as offshored if the employer and the worker are located in different countries. As noted in Section 2, the US is the country with the majority of employers in the data. In what follows, we use the US as our benchmark country and measure the share of jobs that US employers offshore in each occupation. With this in mind, we assign the jobs in the workers' job-histories to occupations listed in the workers profiles. For each of the 91 detailed occupations in the worker-profiles, we compute the value share of US jobs performed by non-US workers:

$$\mathcal{O}^j = \frac{\text{value of jobs in } j \text{ where cty. employer} = \text{US and cty. worker} \neq \text{US}}{\text{value of all jobs in } j \text{ where cty. employer} = \text{US}}. \qquad (22)$$

The expression in (22) measures the share of the wage bill that is offshored from the US to the rest of the world in occupation j.[25] Appendix A.5 reports an alternative measure that captures the share of jobs that are offshored. The results are consistent across measures.

5.2 Results

Table 3 reports the measure in (22) for the most and least frequently offshored occupations in the platform. The data on cross-border contracts suggests that whether a job can be performed remotely is an imperfect proxy of the likelihood that the job is offshored. For example, only 24% of corporate law jobs are offshored, even though all of them are performed remotely. In fact, there is substantial heterogeneity across occupations. For

[25]In Section 4.1, we denoted the share of the wage bill earned by US workers as s^j_{us}. In this section, we write $\mathcal{O}^j$ instead of $1 - s^j_{us}$ to highlight that our empirical measure in (22) is based on jobs whose employers are in the US (i.e., those that are offshored from a US perspective). We note that, in the model, the remote good is perfectly tradeable, so the model is consistent with employers being located anywhere, including the US.

example, Technical Support jobs are three times more likely to be offshored than Grant Writers jobs. Again, this is in spite of the fact that all the jobs in the platform are performed remotely. We compute how frequently are jobs offshored for the Standard Occupational Classification (SOC) categories represented in our data, and report these results in Appendix Table A9.

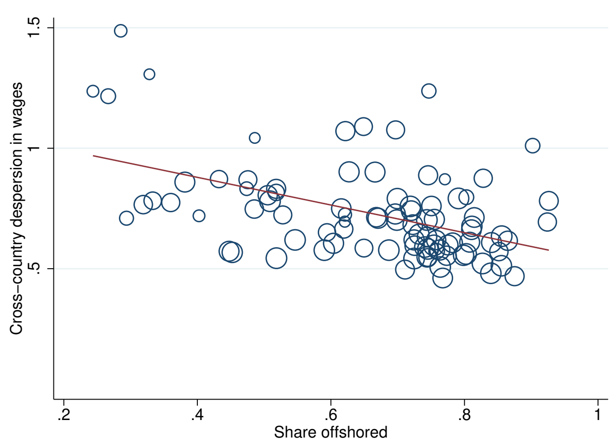
Table 3: Most and least offshored occupations

Most offshored		Least offshored	
Technical Support Representatives	0.93	Corporate Law	0.24
ERP / CRM Specialists	0.92	Contract Law	0.29
Medical Translators	0.88	Grant Writers	0.29
Legal Translators	0.87	Intellectual Property Law	0.33
Mobile Developers	0.86	Resumes & Cover Letters Writer	0.33

Notes: The Table reports the measure defined in equation (22) for the Top 5 and Bottom 5 occupations.

Figure 6 plots the value share of jobs offshored (x-axis) and the cross-country standard deviation in log wages within each occupation (y-axis). There is a clear negative relationship between the two: Wages are less dispersed across countries in more frequently offshored occupations. This correlation suggests that offshoring may play a role in equalizing remote wages across countries.

Figure 6: Offshoring and cross-country wage dispersion



Notes: Each circle represents an occupation. The figure compares the measure in equation (A.5.1) to the cross-country standard deviation in average (log) wages within each occupation. Circle sizes represent the number of countries with workers in the occupation. The estimated slope is -0.47 (0.11) and the R-squared is 0.18.

6 Conclusion

This paper uses novel data from a large web-based job platform to study how the price of remote work is determined in a globalized labor market. Despite the global nature of the platform, we find large wage gaps that are strongly correlated with the GDP per capita of the workers' country, and are not accounted for by differences in workers' characteristics, occupations, or by differences in the employers' locations. Data on wage changes suggests that this correlation is driven by differences in the wages and prices that remote workers face in their local labor markets. We also document that remote wages in local currency move with the dollar exchange rate of the worker's country, and are highly sensitive to changes in the wages of foreign competitors. Finally, we provide a new measure of which jobs are more frequently offshored based on the prevalence of actual cross-border contracts rather than subjective job characteristics.

These findings have profound implications on how the rise of remote work may impact wages across the world. First, remote wages are more equalized than local wages across countries, but the wage gaps across locations are still large. Second, there is a high pass-through from the exchange rate to local currency remote wages in countries other than the US. These two facts are strikingly similar to findings obtained in the literature that looks at tradable goods prices, suggesting that remote work can potentially integrate service markets in similar ways that trade has tended to globalize goods markets. Finally, we show that whether a job is performed remotely is an imperfect proxy for whether a job is at risk of being offshored. Future work on how to measure offshorability should take this into account.

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Online Appendix

A.1 Additional Tables and Figures

Table A1: List of Occupations

Detailed occupation	Broad Occ.	Detailed occupation	Broad Occ.
Accounting Freelancers	Accounting	Brand Identity Strategy Freelancers	Design
Financial Planners & Advisors	Accounting	Graphics Design Freelancers	Design
HR & Recruiting Professionals	Accounting	Logo & Brand Designers	Design
Management Consultants	Accounting	Motion Graphics Freelancers	Design
Other - Accounting & Consulting Specialists	Accounting	Other - Design & Creative	Design
Data Entry Specialists	Admin	Photographers	Design
Other - Admin Support Professionals	Admin	Physical Design Freelancers	Design
Project Managers	Admin	Presentation Designers & Developers	Design
Transcription Services Professionals	Admin	Video Production Specialists	Design
Virtual Assistants, Personal Assistants	Admin	Voice Talent Artists	Design
Web Research Specialists	Admin	3D Modeling Cad Freelancers	Engineering
Customer Service & Tech Support Reps	Customer Service	Architects	Engineering
Other - Customer Service Specialists	Customer Service	Chemical Engineers	Engineering
Technical Support Representatives	Customer Service	Contract Manufacturers	Engineering
A/B Testing Specialists	Data Science	Electrical Engineers	Engineering
Data Extraction / ETL Specialists	Data Science	Interior Designers	Engineering
Data Mining Management Freelancers	Data Science	Mechanical Engineers	Engineering
Data Visualization Specialists & Analysts	Data Science	Other - Engineering & Architecture Specialists	Engineering
Machine Learning Specialists & Analysts	Data Science	Product Designers	Engineering
Other - Data Science & Analytics Professionals	Data Science	Structural & Civil Engineers	Engineering
Quantitative Analysis Specialists	Data Science	Database Administration Freelancers	IT
Animators	Design	ERP / CRM Implementation Specialists	IT
Art Illustration Freelancers	Design	Information Security Specialists & Consultants	IT
Audio Production Specialists	Design	Network & System Administrators	IT
		Other - IT & Networking	IT

Table A1: (cont.) List of Occupations

Detailed occupation	Broad Occ.	Detailed occupation	Broad Occ.
Contract Law Freelancers	Legal	Desktop Software Developers	Web & soft.
Corporate Law Professionals & Consultants	Legal	E-commerce Programmers & Developers	Web & soft.
Criminal Law Professionals & Consultants	Legal	Game Developers	Web & soft.
Family Law Professionals & Consultants	Legal	Mobile Developers	Web & soft.
Intellectual Property Law Professionals & Consultants	Legal	Other Software Development Freelancers	Web & soft.
Other Legal Freelancers	Legal	Product Management Professionals & Consultants	Web & soft.
Paralegal Professionals	Legal	QA & Testing Specialists	Web & soft.
Display Advertising Specialists	Sales	Scripts & Utilities Developers	Web & soft.
Email & Marketing Automation Managers & Consultants	Sales	Web Designers, Mobile Designers	Web & soft.
Lead Generation Professionals	Sales	Web Developers	Web & soft.
Market Researchers, Customer Researchers	Sales	Academic Writers & Researchers	Writing
Marketing Strategy Freelancers	Sales	Article Blog Writing Freelancers	Writing
Other Sales & Marketing Specialists	Sales	Copywriters	Writing
Public Relations (PR) Professionals	Sales	Creative Writers	Writing
Search Engine Marketing (SEM) Specialists	Sales	Grant Writers	Writing
Search Engine Optimization (SEO) Specialists	Sales	Other Writing Services Professionals	Writing
Social Media Marketing (SMM) Specialists	Sales	Proofreaders & Editors	Writing
Telemarketing & Telesales Specialists	Sales	Resumes & Cover Letters Writers	Writing
General Translation Freelancers	Translation	Technical Writers	Writing
Legal Translation Professionals	Translation	Web Content Writers, Web Content Managers	Writing
Medical Translators Professionals	Translation		
Technical Translation Professionals	Translation		

Table A2: Concordance between occupations in the Platform and SOC classification

Occupation Platform	SOC code	SOC title	Occupation Platform	SOC code	SOC tittle
3D Modeling Cad Freelancers	27-1014	Special Effects Artists and Animators	Logo & Brand Designers	27-1024	Graphic Designers
A/B Testing Specialists	15-1250	Software and Web Developers, Programmers	Machine Learning Specialists & Analysts	15-2051	Data Scientists
Accounting Freelancers	13-2011	Accountants and Auditors	Management Consultants	13-1111	Management Analysts
Animators	27-1014	Special Effects Artists and Animators	Market Researchers, Customer Researchers	13-1161	Market Research Analysts and Mktg Spec.
Architects	17-1011	Architects, Except Landscape and Naval	Marketing Strategy Freelancers	13-1161	Market Research Analysts and Mktg Spec.
Art Illustration Freelancers	27-1013	Fine Artists	Mechanical Engineers	17-2141	Mechanical Engineers
Article Blog Writing Freelancers	27-3043	Poets, Lyricists and Creative Writers	Medical Translators Professionals	27-3091	Interpreters and Translators
Audio Production Specialists	27-4011	Audio and Video Technicians	Mobile Developers	15-1252	Software Developers
Chemical Engineers	17-2041	Chemical Engineers	Network & System Administrators	15-1244	Network and Computer Systems Admin.
Contract Law Freelancers	23-1011	Lawyers	Other - Admin Support Professionals	43-4151	Order Clerks
Contract Manufacturers	17-3011	Architectural and Civil Drafters	Other Sales & Marketing Specialists	13-1161	Search Marketing Strategists
Copywriters	27-3043	Writers and Authors	Other Writing Services Professionals	27-3043	Writers and Authors
Corporate Law Professionals & Consultants	23-1011	Lawyers	Paralegal Professionals	23-2011	Paralegals and Legal Assistants
Creative Writers	27-3043	Poets, Lyricists and Creative Writers	Photographers	27-4021	Photographers
Customer Service & Tech Support Reps	43-4051	Customer Service Representatives	Presentation Designers & Developers	27-1011	Art Directors
Data Entry Specialists	43-9021	Data Entry Keyers	Product Management Professionals & Consultants	13-1081	Logistics Analysts
Data Extraction / ETL Specialists	15-1243	Data Warehousing Specialists	Project Managers	13-1082	Project Management Specialists
Data Mining Management Freelancers	15-2051	Data Scientists	Proofreaders & Editors	27-3041	Editors
Data Visualization Specialists & Analysts	15-2051	Data Scientists	Public Relations (PR) Professionals	27-3031	Public Relations Specialists
Database Administration Freelancers	15-1242	Database Administrators	QA & Testing Specialists	15-1253	Software Quality Assurance Analysts
Desktop Software Developers	15-1252	Software Developers	Quantitative Analysis Specialists	15-2051	Data Scientists
Display Advertising Specialists	13-1161	Search Marketing Strategists	Resumes & Cover Letters Writers	21-1012	Educational, Guidance, and Career Counselors
ERP / CRM Implementation Specialists	15-1211	Computer Systems Analysts	Scripts & Utilities Developers	15-1251	Computer Programmers
Ecommerce Programmers & Developers	13-1161	Search Marketing Strategists	Search Engine Marketing (SEM) Specialists	13-1161	Search Marketing Strategists
Electrical Engineers	17-2071	Electrical Engineers	Search Engine Optimization (SEO) Specialists	13-1161	Market Research Analysts and Mktg Spec.
Email & Marketing Automation Managers & Consultants	13-1161	Search Marketing Strategists	Social Media Marketing (SMM) Specialists	13-1161	Search Marketing Strategists
Family Law Professionals & Consultants	23-1011	Lawyers	Technical Support Representatives	15-1232	Computer User Support Specialists
Game Developers	15-1255	Video Game Designers	Technical Translation Professionals	27-3091	Interpreters and Translators
General Translation Freelancers	25-1124	Foreign Lang. and Literature Teachers, PSE	Technical Writers	27-3042	Technical Writers
Grant Writers	13-1131	Fundraisers	Telemarketing & Telesales Specialists	41-9041	Telemarketers
Graphics Design Freelancers	27-1024	Graphic Designers	Transcription Services Professionals	27-4011	Audio and Video Technicians
Information Security Specialists & Consultants	15-1212	Information Security Analysts	Video Production Specialists	27-2012	Producers and Directors
Intellectual Property Law Professionals & Consultants	23-1011	Lawyers	Virtual Assistants, Personal Assistants	27-1014	Special Effects Artists and Animators
Interior Designers	27-1025	Interior Designers	Voice Talent Artists	27-2042	Musicians and Singers
Lead Generation Professionals	11-2021	Marketing Managers	Web Designers, Mobile Designers	15-1255	Web and Digital Interface Designers
Legal Translation Professionals	27-3091	Interpreters and Translators	Web Research Specialists	15-2051	Data Scientists

Table A3: Wage determinants

	Coef.	Std. Err.		Coef.	Std. Err.
Experience			**Quality ratings**		
Earnings (in logs)	0.0723***	(0.00175)	Top rated	0.132***	(0.0048)
<=5 jobs	-0.0424***	(0.00578)	SR <70%	-0.167***	(0.0229)
[6,15) jobs	-0.0610***	(0.00625)	SR [70%,80%)	-0.0745***	(0.0165)
[15,50) jobs	-0.0390***	(0.00771)	SR [80%,90%)	-0.0773***	(0.0130)
>=50 jobs	-0.00258	(0.0172)	SR [90%,95%)	-0.0497***	(0.0128)
Part time/full time			SR [95%,100%)	-0.0380***	(0.0124)
As needed	0.141***	(0.0108)	SR 100%	-0.100***	(0.0120)
<= 30 hrs/week	0.0982***	(0.0117)	**Skills**		
> 30 hrs/week	0.0779***	(0.0105)	# test	-0.0018***	(0.0003)
Response time			Av. score	0.0581***	(0.00542)
< 24 hrs	-0.0415***	(0.00861)	**Agency**		
< 3 days	0.0781***	(0.00507)	Single worker	0.148***	(0.0125)
3+ days	0.0572***	(0.0145)	Multi worker	-0.0437***	(0.0134)
Observations	90,550	$\mathbf{R^2}$	0.551		

Notes: The table reports the coefficients estimated from equation (1). The sample size includes the pairs worker-employer with available transacted wage data. *: significant at the 10% level, **: significant at the 5% level, *** significant at the 1% level.

Table A4: Variance decomposition of wages

Component	Share of variance
Country of worker	0.23
Country of employer	0.004
Controls	0.17
Cov (country of worker - controls)	0.15
Cov (country of employer - controls)	0.0008
Cov (country of employer - country of worker)	0.002
Residual	0.45

Notes: The Table reports the variance decomposition of equation (1) using transacted wages. Rows (1)-(3) show the variance accounted by the country of worker $\mathbb{C}_i$, the country of employer $\mathbb{D}_f$, and the controls $\mathbb{I}_{i=f}$ and $\boldsymbol{\beta' X_i}$. Rows (4) and (5) show two times the covariance between $\mathbb{C}_i$ and controls and between $\mathbb{D}_f$ and controls, respectively. Rows (7) shows two times the covariance between $\mathbb{C}_i$ and $\mathbb{D}_f$. Row (7) is the variance not explained.

Table A5: Frequency of transacted wage changes

Sample	Freq. Wage Changes	Share Wage Increases	Med. Wage Increase	Med. Wage Decrease
All	0.76	0.64	0.25	-0.22
$\Delta T = 1$	0.69	0.58	0.22	-0.22
$\Delta T \leq med(\Delta T)$	0.71	0.60	0.22	-0.22
$\Delta T > med(\Delta T)$	0.82	0.68	0.29	-0.22

Notes: The Table presents summary statistics about the distribution of transacted wage changes in between subsequent hourly jobs.

Table A6: Pass-through to transacted wages: First Stage

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	$\Delta_s w_{jt}$	$\Delta_s w_{jt}$	$\Delta_s w_{jt}$	$\Delta_s w_{-ijt}$	$\Delta_s w_{jt}$	$\Delta_s w_{jt}^{plac}$	$\Delta_s w_{jt}$	$\Delta_s w_{jt}$
$\Delta_s e_{ct}$	-0.003		-0.006	-0.004	-0.003	0.002	-0.002	0.019
	(0.017)		(0.017)	(0.017)	(0.017)	(0.004)	(0.016)	(0.017)
π_{c,t_s}	-0.010		-0.013	-0.010	-0.010	0.008	-0.008	-0.001
	(0.026)		(0.026)	(0.026)	(0.026)	(0.021)	(0.021)	(0.048)
$\pi_{c,t_s} + \Delta_s e_{ct}$		-0.003						
		(0.017)						
$\Delta_s e_t$	0.688***	0.688***	0.757***	0.691***	0.688***	0.028	0.552***	0.100***
	(0.116)	(0.115)	(0.115)	(0.118)	(0.116)	(0.035)	(0.112)	(0.027)
$\pi_{t-s,t}$	-0.178	-0.187	-0.109	-0.162	-0.178	-0.347***	-1.100***	0.470***
	(0.175)	(0.170)	(0.182)	(0.177)	(0.175)	(0.065)	(0.143)	(0.146)
$\Delta_s e_t^{plac}$					0.000	-0.009***		
					(0.000)	(0.002)		
$\pi_{t-s,t}^{plac}$					0.001	-0.351***		
					(0.003)	(0.045)		
Observations	88399	88399	66526	88399	88399	88399	88399	88399

Notes: Columns 1 reports the first stage corresponding to Column 3 in Table (2). Columns 2-4 report the first stage corresponding to Columns 2-4 in Table (A7). Columns 5-6 report the first stage corresponding to Column 5 in Table (A7). Columns 7-8 report the first stage corresponding to Columns 6-7 in Table (A7). Specifications in these columns include country-sector-specific linear trends but they are not reported. Standard errors are clustered at the sector-time-spell and country level. *: significant at the 10% level, **: significant at the 5% level, *** significant at the 1% level.

Table A7: Pass-through to transacted wages: Robustness

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	$\Delta_s w_{ijt}$	$\Delta_s w_{ijt}$	$\Delta_s w_{ijt}$	$\Delta_s w_{ijt}$	$\Delta_s w_{ijt}$	$\Delta_s w_{ijt}$	$\Delta_s w_{ijt}$	$\Delta_s w_{ijt}$
$\Delta_s e_{ct}$			0.251***	0.214***	0.213***	0.183**	0.232***	0.084***
			(0.067)	(0.053)	(0.053)	(0.087)	(0.080)	(0.028)
π_{c,t_s}			0.240*	0.195*	0.196*	0.217	0.248	0.095
			(0.137)	(0.103)	(0.104)	(0.206)	(0.160)	(0.086)
$\pi_{c,t_s} + \Delta_s e_{ct}$	0.203***	0.213***						
	(0.058)	(0.053)						
$\Delta_s w_{jt}$		0.748***	0.804***		0.737***	1.089***	-0.398	
		(0.260)	(0.282)		(0.250)	(0.230)	(0.544)	
$\Delta_s w_{-ijt}$				0.741***				
				(0.252)				
$\Delta_s w_{jt}^{plac}$					0.062			
					(0.103)			
Observations	88399	88399	66526	88399	88399	88399	88399	226559
Test $\beta_1 = \beta_2$			0.93	0.84	0.85	0.86	0.88	0.90
Specification	OLS	2SLS	2SLS	2SLS	2SLS	2SLS	2SLS	OLS
F stat 1st stage		34.0	48.3	37.2	33.9	193.1	7.01	

Notes: Columns 1-2 reestimate Columns 1 and 3 from Table 2 imposing the restriction that $\beta_1 = \beta_2$. Column 3 reestimates Column 3 in Table 2 using the sample of non-zero wage changes. Column 4 reestimates Column 3 in Table 2 replacing the baseline wage index $\Delta_s W_{jt}$ for the leave-one-out wage index $\Delta_s W_{-ijt} \equiv \sum_{l \neq i} \frac{s_{ljt}}{1-s_{ijt}} \Delta_s w_{lt} = \left[\Delta_s W_{jt} - s_{ijt}\Delta_s w_{ijt}\right] / \left[1 - s_{ijt}\right]$. This alternative specification alleviates the concern that the aggregate wage index $\Delta_s W_{jt}$ is by definition a function of each worker's wage, and is thus correlated with the error term. Column 5 reestimates Column 3 in Table 2 and includes the change in wages of workers that are predicted to be the least likely competitors of a given worker. These columns include country-sector-specific linear trends. Column 6 reestimates the specification in Columns 3 of Table 2 without controlling for country-sector-specific trends. Column 7 reestimates the specification in Column 3 of Table 2 without controlling for time-spell fixed effects. In Columns 1-7, standard errors are clustered at the sector-time-spell and country level. Column 8 reports the results from estimating equation (21). Standard errors are clustered at the country level. *: significant at the 10% level, **: significant at the 5% level, *** significant at the 1% level. The corresponding first stage regressions are reported in Table A6.

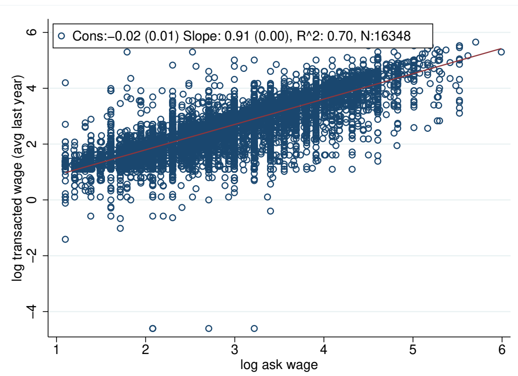
Table A8: Offshoring by occupation in the Platform

Occupation Platform	Value share offshored	Quantity share offshored	Occupation Platform	Value share offshored	Quantity share offshored
Technical Support Representatives	0.93	0.89	Lead Generation Professionals	0.72	0.87
ERP / CRM Implementation Specialists	0.92	0.95	Presentation Designers & Developers	0.72	0.82
Medical Translators Professionals	0.88	0.90	Architects	0.71	0.89
Legal Translation Professionals	0.86	0.88	Video Production Specialists	0.70	0.81
Mobile Developers	0.86	0.90	Logo & Brand Designers	0.70	0.81
Interior Designers	0.85	0.90	Data Mining Management Freelancers	0.70	0.89
Technical Translation Professionals	0.84	0.87	Photographers	0.70	0.83
General Translation Freelancers	0.84	0.88	Project Managers	0.69	0.79
Machine Learning Specialists & Analysts	0.83	0.89	Email & Marketing Automation Managers & Consultants	0.67	0.80
Virtual Assistants, Personal Assistants	0.83	0.88	Market Researchers, Customer Researchers	0.67	0.83
QA & Testing Specialists	0.81	0.80	Audio Production Specialists	0.67	0.76
Web Research Specialists	0.81	0.87	Mechanical Engineers	0.65	0.81
Animators	0.81	0.89	Data Visualization Specialists & Analysts	0.62	0.77
Network & System Administrators	0.81	0.87	Contract Manufacturers	0.62	0.80
Information Security Specialists & Consultants	0.80	0.88	Chemical Engineers	0.62	0.71
Data Entry Specialists	0.80	0.88	Technical Writers	0.62	0.64
Desktop Software Developers	0.80	0.87	Marketing Strategy Freelancers	0.60	0.76
Ecommerce Programmers & Developers	0.79	0.85	Electrical Engineers	0.59	0.80
Scripts & Utilities Developers	0.78	0.81	Copywriters	0.59	0.61
Product Management Professionals & Consultants	0.77	0.84	Proofreaders & Editors	0.55	0.56
Family Law Professionals & Consultants	0.77	0.56	Accounting Freelancers	0.53	0.68
Customer Service & Tech Support Reps	0.76	0.83	Article Blog Writing Freelancers	0.52	0.57
3D Modeling Cad Freelancers	0.76	0.87	A/B Testing Specialists	0.52	0.76
Other - Admin Support Professionals	0.75	0.87	Voice Talent Artists	0.52	0.55
Web Designers, Mobile Designers	0.75	0.84	Quantitative Analysis Specialists	0.51	0.70
Search Engine Marketing (SEM) Specialists	0.75	0.83	Display Advertising Specialists	0.49	0.64
Data Extraction / ETL Specialists	0.75	0.87	Creative Writers	0.45	0.48
Transcription Services Professionals	0.75	0.78	Other Writing Services Professionals	0.45	0.51
Telemarketing & Telesales Specialists	0.74	0.85	Paralegal Professionals	0.40	0.36
Social Media Marketing (SMM) Specialists	0.74	0.86	Public Relations (PR) Professionals	0.38	0.57
Graphics Design Freelancers	0.74	0.82	Management Consultants	0.36	0.53
Search Engine Optimization (SEO) Specialists	0.74	0.83	Resumes & Cover Letters Writers	0.33	0.35
Other Sales & Marketing Specialists	0.73	0.84	Intellectual Property Law Professionals & Consultants	0.33	0.38
Game Developers	0.73	0.88	Grant Writers	0.29	0.30
Database Administration Freelancers	0.72	0.84	Contract Law Freelancers	0.29	0.33
Art Illustration Freelancers	0.72	0.79	Corporate Law Professionals & Consultants	0.24	0.33

Table A9: Offshoring by SOC occupation

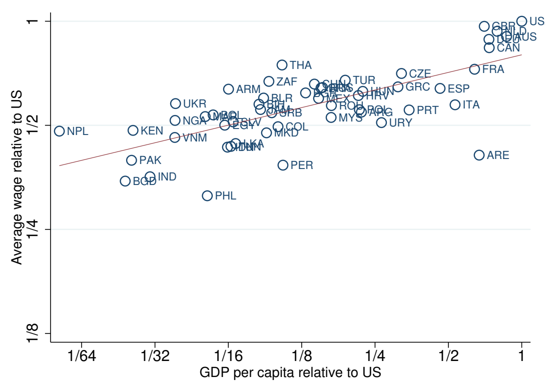
SOC code	SOC title	Value share offshored	SOC code	SOC title	Value share offshored
15-1232	Computer User Support Specialists	0.93	27-1011	Art Directors	0.72
15-1211	Computer Systems Analysts	0.92	13-1161	Search Marketing Strategists	0.72
27-3091	Interpreters and Translators	0.85	13-1161	Market Research Analysts and Marketing Specialists	0.72
27-1025	Interior Designers	0.85	17-1011	Architects, Except Landscape and Naval	0.71
25-1124	Foreign Language and Literature Teachers, Postsecondary	0.84	27-2012	Producers and Directors	0.70
15-1252	Software Developers	0.83	27-4021	Photographers	0.70
15-1253	Software Quality Assurance Analysts and Testers	0.81	13-1082	Project Management Specialists	0.69
27-1014	Special Effects Artists and Animators	0.81	17-2141	Mechanical Engineers	0.65
15-1244	Network and Computer Systems Administrators	0.81	17-3011	Architectural and Civil Drafters	0.62
15-1212	Information Security Analysts	0.80	17-2041	Chemical Engineers	0.62
43-9021	Data Entry Keyers	0.80	27-3042	Technical Writers	0.62
15-1251	Computer Programmers	0.78	17-2071	Electrical Engineers	0.59
13-1081	Logistics Analysts	0.77	27-3041	Editors	0.55
43-4051	Customer Service Representatives	0.76	13-2011	Accountants and Auditors	0.53
43-4151	Order Clerks	0.75	15-1250	Software and Web Developers, Programmers, and Testers	0.52
15-1255	Video Game Designers	0.75	27-2042	Musicians and Singers	0.52
15-1255	Web and Digital Interface Designers	0.75	27-3043	Poets, Lyricists and Creative Writers	0.50
15-1243	Data Warehousing Specialists	0.75	27-3043	Writers and Authors	0.50
41-9041	Telemarketers	0.74	23-2011	Paralegals and Legal Assistants	0.40
15-2051	Data Scientists	0.74	23-1011	Lawyers	0.39
27-1024	Graphic Designers	0.73	27-3031	Public Relations Specialists	0.38
15-1242	Database Administrators	0.72	13-1111	Management Analysts	0.36
27-1013	Fine Artists, Including Painters, Sculptors, and Illustrators	0.72	21-1012	Educational, Guidance, and Career Counselors and Advisors	0.33
27-4011	Audio and Video Technicians	0.72	13-1131	Fundraisers	0.29
11-2021	Marketing Managers	0.72			

Figure A.1: Ask vs. transacted wages



Notes: The figure shows the scatter plot between a worker's ask wage (x-axis) and the worker's average transacted wage (y-axis). Average transacted wages are computed using wages that were received within the year around the date of the ask wage.

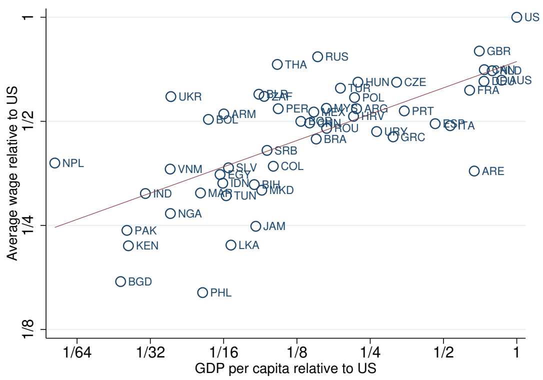
Figure A.2: Average wages across workers: Ask wages



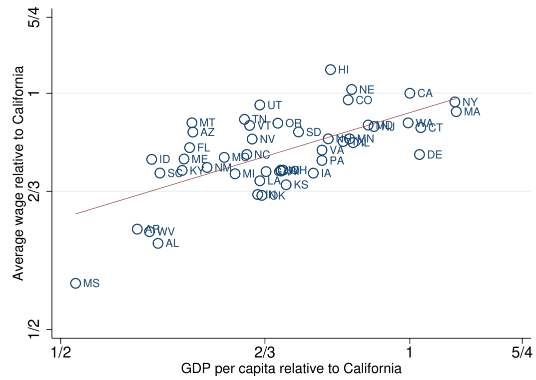
Notes: The x-axis reports the (log of) the relative GDP per capita in US dollars, taken from the World Development Indicators (WDI). It plots the residualized average wage in each country relative to the US obtained from the worker's country fixed effects estimated in equation (1). The outcome variable is ask wages, as opposed to transacted wages. The red lines show the linear fit of the data. The estimated slope is 0.17 (0.03) and the R^2 is 0.50.

Figure A.3: Average wages (non-residualized) across workers

(a) By country



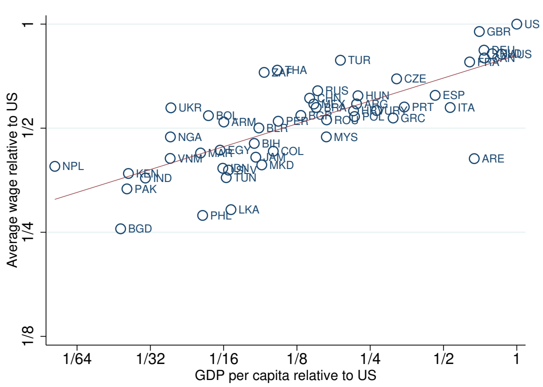
(b) By US states



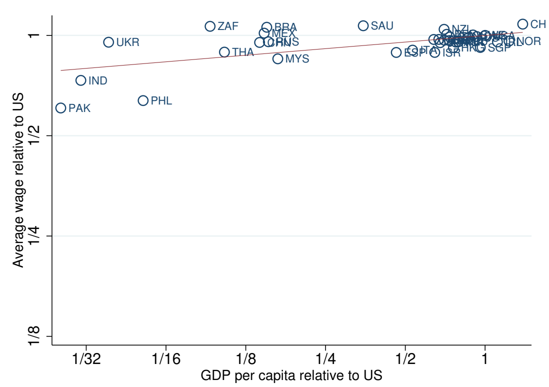
Notes: The x-axis in panel (a) reports the (log of) the relative GDP per capita in US dollars, taken from the World Development Indicators (WDI). The y-axis plots the average transacted wage in each country relative to the US. The estimated slope is 0.25 (0.04) and the R-squared is 0.47. The x-axis in panel (b) reports the (log of) the relative GDP per capita in US dollars, taken from the Bureau of Economic Analysis. The y-axis plots the average transacted wage in each state relative to California. The estimated slope is 0.44 (0.09) and the R-squared is 0.43. The red lines show the linear fit of the data.

Figure A.4: Wages and GDP per capita relative to the US: controlling for distance

(a) Country of worker



(b) Country of employer



Notes: The x-axes report the (log of) the relative GDP per capita in US dollars, taken from the World Development Indicators (WDI). The figure reports the average residualized wage in each country relative to the US obtained from the country fixed effects. These worker' and employer's country fixed effect are estimated according to equation (1) with the following additional control variables: a dummy variable for whether the country of the employer and worker are contiguous, have common language, have colony ties, common currency, and common legal origin. It also controls for the distance in kilometers between the capital cities of both countries weighted by the population size, and the number of hours difference between both countries. Panel (a) plots the worker's country fixed effects and panel (b) plots the employer's country fixed effects. The estimated slope in panel (a) is 0.22 (0.03) and the R-squared is 0.58. The estimated slope in panel (b) is 0.07 (0.02) and the R-squared is 0.36.

Figure A.5: Real wages and comparison with non-remote wages

(a) Remote vs. non-remote wages

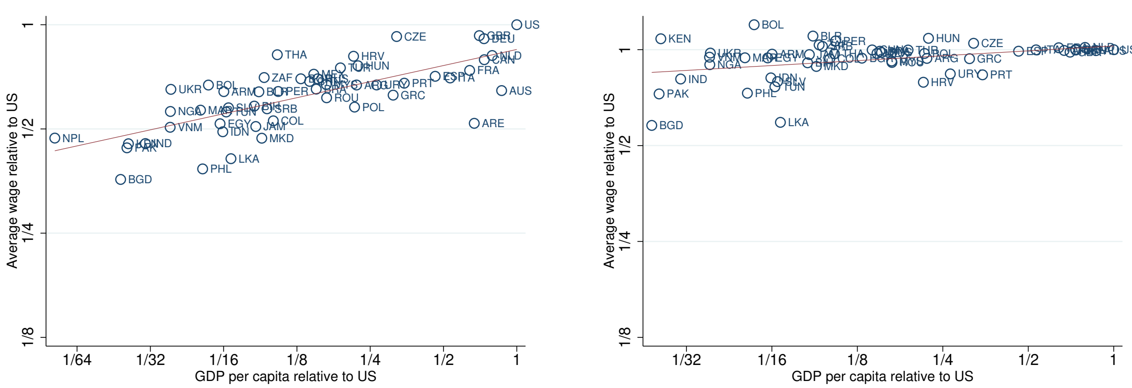
(b) Remote wages and domestic price levels

Notes: The x-axis of panel (a) reports the average (log of) compensation of employees in 2011 denominated in US dollars. The average compensation for each country is computed as the average among the following occupations included in the Comparison Program (ICP) from the World Bank: Accounting and Bookkeeping Clerks, HR Professionals, Computer Operator, Data Processing Manager, and Database Administrator. Panel (a) plots the average wage residualized in each country relative to the US. The x-asis of panel (b) reports the price level of output included in the ICP (PPP/XR, where the price level of output of USA in 2017 equals 1), relative to the US. The y-axes reports average residualized wage obtained are from the country fixed effects estimated in equation (1). The red lines show the linear fit of the data. The estimated slope is 0.18 (0.04) and the R-squared is 0.41 in panel a, the estimated slope is 0.52 (0.06) and the R-squared is 0.54.

Figure A.6: Differences in wages within workers and employers

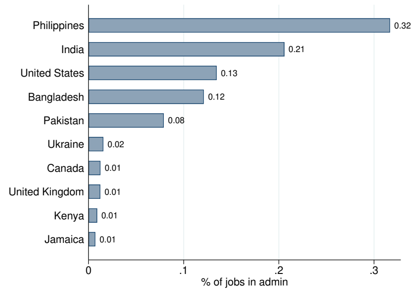
(a) Within employer

(b) Within worker

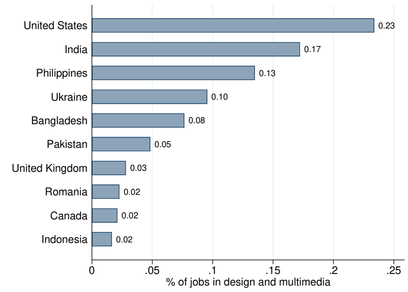


Notes: The x-axis reports the (log of) the relative GDP per capita in US dollars, which we take from the World Development Indicators (WDI). The y-axis in panel (a) reports the set of country-of-worker effect (relative to employers in the US) estimated according a version of equation (1) that controls for employer fixed effects. The estimated slope is 0.15 (0.02) with an R-squared of 0.53. The y-axis in panel (b) reports the set of country-of-employer fixed effect (relative to employers in the US) estimated according to a version of equation (1) that controls for worker fixed effects. The estimated slope is 0.05 (0.02) with an R-squared of 0.14.

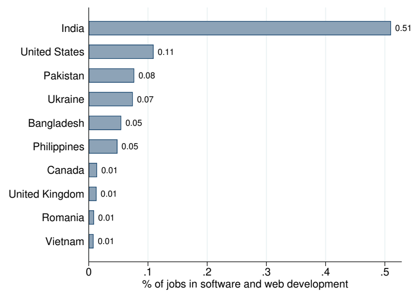
Figure A.7: Sectorial variation in instrumental variable



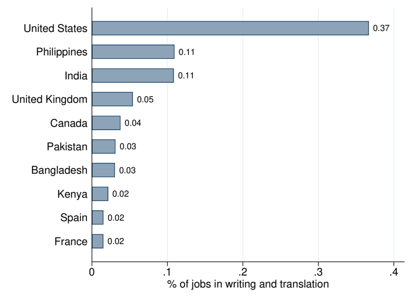
(a) Admin



(b) Design



(c) Web



(d) Writing

Notes: This figure reports the variation behind the sectoral shares s^j_{ct} used to construct the instrumental variable $\sum_c s^j_{ct}\,[\pi_{ct_s} + \Delta_s e_{ct}]$.

A.2 Data Appendix

Additional data sources: Our measure of GDP per capita in current US dollars is the variable gdp_pc_curr for year 2016 from the World Development Indicators (WDI). The GDP per capita in US dollars for each state is the variable SAGDP10N obtained from the U.S. Department of Commerce, Bureau of Economic Analysis for year 2017. The 'gravity' variables obtained from the The CEPII Gravity Database are the following: contig, comlang_off, distw, tdiff, colony, comcur, comleg_pretrans, tradeflow_imf_d, gdp_ppp_o, and gdp_ppp_d (for a detailed description see http://www.cepii.fr/DATA_DOWNLOAD/gravity/doc/Gravity_documentation.pdf). For non-remote wages, we use the compensation of employees for year 2001 from the International Comparison Program (ICP) from the World Bank for the following occupations: Accounting and bookkeeping clerks, HR professionals, Computer operator, Data processing manager, and Database administrator. We adjust the value of compensation by the current exchange rate to convert it into dollars. Finally, the exchange rate and inflation data used in section 4 is sourced from the International Financial Statistics (IFS) database from the IMF.

Algorithm: The data on job history used in section 4.2 specify the sector for a subset of jobs. We assign sectors to the remaining jobs using the information from the jobs' descriptions using a machine-learning algorithm. We first make the data suitable for analysis by removing a set of stop-words (e.g., "and", "the", etc.), punctuation marks and numbers from the job description, which is available for all jobs. Then, we keep the 3,000 most frequent words, which balances the desire to use as many words as possible in the prediction step without overfitting the data. Next, we keep 70% of jobs with occupation data as a training sample, and use the remaining 30% as a validation sample. We then train an artificial neural network on the training sample using a hyper-parameter optimization algorithm (see Chollet, 2021) to predict the broad occupation a given job belongs to based on the (cleaned) job description. To set the parameters of this algorithm, we follow a cross-validation exercise in order to achieve good prediction outcomes on the validation sample. Finally, we apply the estimated prediction model on the descriptions of jobs for which we do not have occupation data and obtain the likelihood that a given job belongs to each broad occupation. In our baseline analysis, we assign jobs to the occupation that obtains the highest likelihood.

A.3 Derivation of Equations (15) and (16)

The change in worker's i wage is:

$$dw^j_{it} = d\omega^j_{ct} + dz^j_{it}, \tag{A.3.1}$$

where the change in wages per efficiency units is given by

$$d\omega_{ct}^j = \frac{\theta}{\rho+\theta} db_{ct}^j + \frac{1}{\rho+\theta} d\varphi_{ct}^j + \frac{\rho-\eta}{\rho+\theta} d\omega_t^j + \frac{1}{\rho+\theta}\left[\eta dp_t + dy_t\right]. \tag{A.3.2}$$

Differentiating (7) yields

$$d\omega_t^j = \sum s_{ct}^j d\omega_{ct}^j - \sum s_{ct}^j da_{ct}^j,$$

which substituting for (A.3.2) can be rewritten as

$$d\omega_t^j = \frac{\theta}{\theta+\eta} db_t^j + \frac{1}{\theta+\eta} d\varphi_t^j - \frac{\rho+\theta}{\theta+\eta} da_t^j + \frac{1}{\theta+\eta}\left[\eta dp_t + dy_t\right]. \tag{A.3.3}$$

Substituting (14) into (A.3.2) and (A.3.3) yields:

$$d\omega_{ct}^j = \frac{\theta}{\rho+\theta}\left[de_{ct} + \pi_{ct}\right] + \frac{1}{\rho+\theta}\left[d\varphi_{ct} + \theta\gamma_{ct}^j\right] + \frac{\rho-\eta}{\rho+\theta}\omega_t^j + \frac{1}{\rho+\theta}\left[\eta p_t + y_t\right].$$

and

$$d\omega_t^j = \frac{\theta}{\theta+\eta}\left[de_{ct} + \pi_{ct}\right] + \frac{1}{\theta+\eta}\left[d\varphi_t^j - \left[\rho+\theta\right] da_t^j + \theta\gamma_t^j + \eta dp_t + dy_t\right],$$

Let $dz_t^j \equiv \sum s_{ct}^j \mathbb{E}_c dz_{it}^j$. Then, we can write:

$$\begin{aligned} d\omega_t^j &= \sum_c s_{ct}^j \mathbb{E}_c\left[d\omega_{ct}^j + dz_{it}^j\right] - dz_t^j - da_t^j, \\ &= -da_t^j - dz_t^j + \sum_c s_{ct}^j \mathbb{E}_c\left[dw_{it}^j\right], \end{aligned}$$

Finally, we define the index of wage changes as:

$$dw_t^j \equiv \sum_c s_{ct}^j \mathbb{E}_c\left[dw_{it}^j\right].$$

Note that we can write:

$$d\omega_t^j = dw_t^j - dz_t^j - da_t^j, \tag{A.3.4}$$

and

$$dw_t^j = \frac{\theta}{\theta+\eta}\left[de_{ct} + \pi_{ct}\right] + \frac{1}{\theta+\eta}\left[\theta\gamma_{ct}^j + d\varphi_t^j - \left[\rho-\eta\right] da_t^j + \eta dp_t + dy_t\right] + dz_t^j, \tag{A.3.5}$$

Substituting (A.3.2), (A.3.4), and (A.3.5) into (A.3.4), we obtain expressions (15) and (16)with

$$d\psi^j_{ct} \equiv \frac{1}{\rho+\theta}\left[d\varphi_{ct} + \theta\gamma^j_{ct}\right] - \frac{\rho-\eta}{\rho+\theta}\left[da^j_t + dz^j_t\right] + \frac{1}{\rho+\theta}\left[\eta p_t + y_t\right].$$

and

$$d\phi^j_t = \frac{1}{\theta+\eta}\left[\theta\gamma^j_{ct} + d\varphi^j_t - [\rho-\eta]\, da^j_t + \eta dp_t + dy_t\right] + dz^j_t.$$

A.4 Alternative occupation production function

This Appendix derives the structural equations used in our estimation in Section 4 from an alternative model in which workers from different locations are perfect substitutes, but can specialize in the production of different tasks. In particular, we modify the framework in Section 4.1 by assuming that the output of sector j in year t is produced by combining the output of a continuum of tasks indexed by $\omega \in [0,1]$:

$$Y_t^j = \left[\int_0^1 y_t^j (\omega)^{\frac{\sigma_j - 1}{\sigma_j}} d\omega \right]^{\frac{\sigma_j}{\sigma_j - 1}}. \tag{A.4.1}$$

Each task ω can be produced remotely by workers in different locations c. The cost of purchasing task ω from location c is $\Omega_{ct}^j / x_c^j (\omega)$, where Ω_{ct}^j is the wage per efficient unit of labor from location c in sector j and $x_c^j (\omega)^{-1}$ are the number of efficiency units of labor from location c required to produce task ω. This number can be location-task specific, indicating that labor from different locations can be relatively more productive for the production of different tasks. We assume that efficiency units of labor from different locations are perfect substitutes in the production of a task, so tasks are supplied by the lowest cost location. Consequently, the price actually paid in the platform for task ω in sector j is then $p_t^j (\omega) = min \left\{ \frac{\Omega_{1t}^j}{x_1^j(\omega)}, ..., \frac{\Omega_{Nt}^j}{x_N^j(\omega)} \right\}$.

We assume that $x_c^j (\omega)$ is a random variable drawn independently for each ω from a Frechet distribution given by

$$F_c^j (x) \equiv Pr \left(x_c^j (\omega) \leq x \right) = e^{-\tilde{A}_c^j x^{1-\rho}},$$

with shape parameter $\rho > 2$, and scale parameter $\tilde{A}_c^j > 0$. A lower value of ρ implies that the draws $x_c^j (\omega)$ are more dispersed across tasks, so that differences in comparative advantage across tasks is stronger. A larger value of $\tilde{A}_c^j$ implies that workers from a location are likely to be more productive across all tasks.

The distributional assumption implies that the distribution of prices in the platform for task ω, $p_t^j (\omega)$, is also Frechet. This distribution, denoted by $G_t^j(p)$, is given by

$$G_t^j (p) = 1 - \prod_c Pr \left(\frac{\Omega_{ct}^j}{x_c^j (\omega)} > p \right) = 1 - e^{-\Phi_t^j p^{\rho - 1}},$$

with $\Phi_t^j \equiv \sum_c \tilde{A}_c^j \left[\Omega_{ct}^j \right]^{1-\rho}$.

We can now compute the cost function associated to the CES production function (A.4.1). The cost function of sector j in year t is a weighted average of tasks' prices given by

$$\Omega_t^j = \gamma_j \left[\Phi_t^j\right]^{\frac{-1}{\rho-1}}, \tag{A.4.2}$$

where $\gamma_j \equiv \Gamma\left(\frac{\rho-\sigma_j}{\rho-1}\right)^{\frac{1}{1-\sigma_j}}$, and $\Gamma(\cdot)$ is the Gamma function assuming $\sigma_j < \rho$.[26]

The probability that a task with labor requirement $x_c^j(\omega)$ is supplied by location c in sector j is

$$Pr\left(\frac{\Omega_{ct}^j}{x_c^j(\omega)} \le min_{s\neq c}\left\{\frac{\Omega_{st}^j}{x_s^j(\omega)}\right\}\right),$$

which is equal to

$$\prod_{s\neq c} Pr\left(\frac{\Omega_{st}^j}{x_s^j(\omega)} \ge \frac{\Omega_{ct}^j}{x_c^j(\omega)}\right) = \prod_{s\neq c} e^{-\tilde{A}_s^j\left[\frac{\Omega_{st}^j}{\Omega_{ct}^j}x_c^j(\omega)\right]^{1-\rho}}$$
$$= e^{\left[x_c^j(\omega)\right]^{1-\rho}\left[\tilde{A}_c^j - \Phi_t^j\left[\Omega_{ct}^j\right]^{\rho-1}\right]}$$

Integrating across all possible values of $x_c^j(\omega)$, we obtain the probability that location c

[26] Given that the production function of sector j combines tasks with a CES technology, the cost function is given by:

$$\left[\Omega_t^j\right]^{1-\sigma_j} = \int_0^1 p_j(\omega)^{1-\sigma_j} d\omega.$$

The moment generating function for $y = -ln(p)$ is $\mathbb{E}\left(e^{ty}\right) = \Gamma\left(1-\frac{t}{\rho-1}\right)\left[\Phi_t^j\right]^{\frac{t}{\rho-1}}$. Then, $\mathbb{E}\left(e^{-t}\right)^{-1/t} = \Gamma\left(1-\frac{t}{\rho-1}\right)^{-1/t}\left[\Phi_t^j\right]^{\frac{-1}{\rho-1}}$. The expression for the cost function follows by replacing t with $\sigma_j - 1$ (see Eaton and Kortum, 2002).

supplies the task:[27]

$$s^j_{ct} = \frac{\tilde{A}^j_c \left[\Omega^j_{ct}\right]^{1-\rho}}{\Phi^j_t}.$$

Under our distributional assumptions, the probability that a location supplies an individual task coincides with the share of spending on tasks performed from the location (see Eaton and Kortum, 2002). That is,

$$\frac{\tilde{A}^j_c \left[\Omega^j_{ct}\right]^{1-\rho}}{\Phi^j_t} = s^j_{ct} = \frac{\Omega^j_{ct} L^j_{ct}}{\Omega^j_t Y^j_t}.$$

Substituting (A.4.2), we obtain the demand for efficiency units of labor from location c in sector j:

$$L^j_{ct} = \tilde{A}^j_c \gamma_j^{\rho-1} \left[\frac{\Omega^j_{ct}}{\Omega^j_t}\right]^{-\rho} Y^j_t,$$

which coincides with equation (6) with $A^j_c = \left[\tilde{A}^j_c\right]^{\frac{1}{\rho-1}} \gamma_j$.

[27]This integral is given by

$$\begin{aligned} s^j_{ct} &= \int_0^\infty e^{x^{1-\rho}\left[\tilde{A}^j_c - \Phi^j_t \left[\Omega^j_{ct}\right]^{\rho-1}\right]} \tilde{A}^j_c x^{-\rho} \left[\rho-1\right] e^{-\tilde{A}^j_c x^{1-\rho}} dx \\ &= \int_0^\infty e^{-x^{1-\rho}\Phi^j_t \left[\Omega^j_{ct}\right]^{\rho-1}} \tilde{A}^j_c x^{-\rho} \left[\rho-1\right] dx \\ &= \tilde{A}^j_c \left[\rho-1\right] \int_0^\infty x^{-\rho} e^{-x^{1-\rho}\Phi^j_t \left[\Omega^j_{ct}\right]^{\rho-1}} dx. \end{aligned}$$

Define $y \equiv \left[\Omega^j_{ct}\right]^{\rho-1} \Phi^j_t x^{1-\rho}$. Then, $dy = -\left[\Omega^j_{ct}\right]^{\rho-1} \Phi^j_t \left[\rho-1\right] x^{-\rho} dx$. This implies that the previous expression can be rewritten as follows:

$$s^j_{ct} = \frac{\tilde{A}^j_c}{\left[\Omega^j_{ct}\right]^{\rho-1} \Phi^j_t} \int_0^\infty e^{-y} dy = \frac{\tilde{A}^j_c \left[\Omega^j_{ct}\right]^{1-\rho}}{\Phi^j_t}.$$

A.5 Alternative measures of offshoring by occupation

A.5.1 Quantity based measures

Section 5 measures the share of jobs that are offshored in terms of values. Here, we present an alternative measure that computes the share in the number (rather than the value) of jobs that are offshored. In particular, we compute

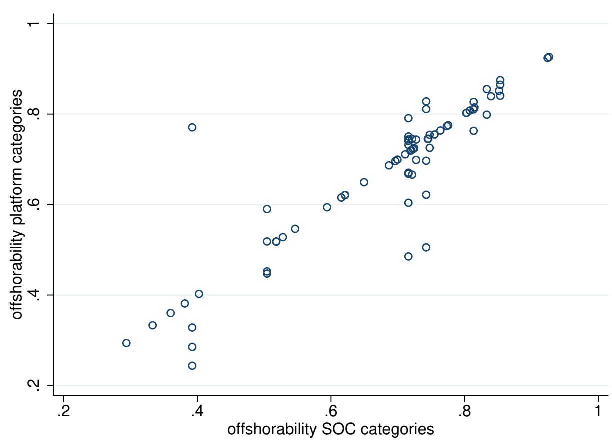
$$\widetilde{\mathcal{O}}^j = \frac{\text{jobs in } j \text{ where cty. employer=US and cty. worker} \neq \text{US}}{\text{All jobs in } j \text{ where cty. employer=US}}. \tag{A.5.1}$$

Appendix Table A8 reports this measure and shows that it is very similar to that in equation (5).

A.5.2 Offshoring across categories in the SOC system

To make our measure easier to use in future research, we compute the fraction of jobs offshored for the SOC categories represented in our data. Figure A.8 plots the measure in (5) when computed for the categories in the platform (y-axis) vs. the SOC categories (x-axis). The categories in the platform are often more disaggregated than those in the SOC, so that the figures often contain many occupations in the y-axis corresponding to one point in the x-axis. The figure shows that, while the measures are positively correlated, the SOC categories are often too broad and mask substantial heterogeneity in the extent that different occupations are being offshored. For example, the SOC category 'Search Marketing Strategists' includes a wide range of more specific occupations in the platform. Within this SOC category, we observe a difference of 30% in the probability of offshoring jobs between 'Ecommerce Programmers and Developers' and 'Display Advertising Spcecialists' ($\mathcal{O}^j = 0.79$ and $\mathcal{O}^j = 0.50$, respectively). This also suggests that having more disaggregated job categories than those currently available in official statistics can help capture better the degree to which different jobs are offshored, and other important dimensions of international labor transactions.

Figure A.8: Offshoring within SOC categories



Notes: Each circle represents an occupation. The figure compares the frequency with which jobs are offshored using equation (22) for SOC categories vs. platform categories.