The International Price of Remote Work*

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Abstract

We use data from a large web-based job platform to study how the price of remote work is determined in a globalized labor market. In the platform, workers from around the world compete for jobs that can be done remotely. We document that, despite the global nature of the marketplace, the worker's location accounts for almost a third of the variance in wages. The observed wage differences are strongly correlated to the GDP per-capita in the worker's location. This correlation is not accounted for by differences in workers' characteristics, occupations, nor for differences in the employers' locations. We also document that remote wages in local currency move almost one-for-one with the dollar exchange rate of the worker's country, and are highly sensitive to changes in the wages of foreign competitors. Finally, we use data on cross-border contracts to document which remote jobs are more frequently offshored.

Keywords: Remote Work, Wages, Exchange rates, PPP, Offshoring.
JEL Codes: F1, F2, F4, F6

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1 Introduction

An increasing number of jobs are being performed remotely, a trend that accelerated dramatically during the COVID pandemic.[1] Remote work can be performed from anywhere, which renders these jobs easy to offshore.[2] By globally integrating labor markets, the rise of remote work can have a profound impact on 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 brings to bear 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 that trade tasks that are delivered remotely, providing a window into a globalized market for remote work.[4] The number of such platforms has tripled over the past decade. By 2020, hundreds of web-based job platforms facilitated millions of international transactions totaling over 50 billion US$ (ILO 2021). The emergence of these platforms has coincided with the dramatic growth in ICT-Enabled Service trade, which has quadrupled in the US since the year 2000 and now accounts for 70% (800 billion US$) of all US service trade.[5]

Our dataset comes 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. The 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

[1] OECD (2021). We use the term remote work to refer to work that does not need to be carried out in-person at specific locations.

[2] See Blinder and Krueger (2013).

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

[4] We follow ILO (2021) and use the term 'web-based' platforms to distinguish platforms where tasks are performed remotely from 'location-based' platforms where tasks are carried out in-person at specific locations (e.g., ride-sharing services).

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

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 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 start by documenting large gaps 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 between a quarter and a third of the variance of wages in the data –more than the variation accounted for by the combination of all other observable worker, employer, and job characteristics–. Remote wages are strongly correlated with GDP per capita: the elasticity of wages with respect to the GDP per capita of the worker's country is 0.21. We also 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 workers' and jobs characteristics, nor by differences in the employers' locations. Instead, the results suggest that remote wages are partly determined by the wages and prices that workers face in their local labor markets. We note, however, that remote wages are substantially more equalized than non-remote wages: the cross-country standard deviation of average wages is only a quarter of the standard deviation of GDP per-capita.

We then study how remote wages respond to international shocks. We start by estimating a standard exchange rate pass-through (ERPT) regression and show that the partial elasticity of dollar wages with respect to the dollar exchange change rate is 14%. This implies that (partial) ERPT into local currency wages is 86%, so that remote wages expressed in local currency move almost one-to-one with the dollar exchange rate. This is in sharp contrast to non-remote wages, which do not typically respond to movements in exchange rates at short horizons. This finding is not mechanically accounted for by remote wages being sticky in dollars, as we obtain a similar elasticity (25% into dollar wages) when focusing on a subsample of dollar wages that do change in a particular period.

We also show that a worker's wage reacts strongly to changes in the wages of other workers in the platform. Since workers are located in different countries, this means that a worker is exposed to international shocks that affect her foreign competitors. Building on standard models of incomplete ERPT, we regress the change in a worker's dollar wage on the change in the worker's dollar opportunity cost (proxied by the inflation and the exchange rate in the worker's country), and an index measuring the wage changes of a worker's competitors. To overcome endogeneity issues, we exploit that workers in different sectors face competitors from different countries, and instrument changes in competitors' wages with the inflation and the exchange rate changes in the competitors' countries. We find that workers adjust their wages almost one-for-one with changes in their foreign competitors' wages. This implies, for example, that, since Indian workers have a combined 20% market share in the platform, a shock that induces a 10% drop in the wages of Indian workers generates a drop of roughly 2% in the wages of US workers.

Finally, we use our data to shed light on which types of jobs or occupations are more likely to be offshored. Existing measures of "offshorability" typically hinge on subjective judgments on the different attributes of a job. Such judgments are often made on the basis of whether a job can be done 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. In contrast, we use our data to directly measure the frequency with which US employers assign contracts to foreign workers in an occupation. In particular, we compute 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 example, only a third of grant writer jobs in the platform are offshored, even though all of them are performed remotely. In fact, there is substantial heterogeneity in the frequency at which jobs are offshored across remote occupations: Interior Design jobs are three times more likely to be offshored than Grant Writers jobs. We also document substantial heterogeneity within categories of the Standard Occupational Classification (SOC) system: for example, within the SOC category "Legal", 96% of jobs in "International law" are offshored, while only 6% in "Tax law" are offshored. Finally, we show that wages are less dispersed in more frequently offshored occupations, providing evidence that offshoring can play a role in equalizing wages across remote workers.

Our paper relates to various strands of the literature. First, it is related 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). A related literature makes international wage comparisons by collecting international wage data for comparable workers. Ashenfelter (2012) documents cross-country wage differentials for McDonalds employees. Hjort et al. (2019) use a dataset on wages paid by multinational firms to show that multinationals' wages around the world are anchored to the level at headquarters. We contribute to this literature by providing international wage comparisons for online occupations that can be done remotely. 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.

Second, 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, good 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 that 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. In addition, our paper is also related to Amiti et al. (2018), who show that prices of manufacturing goods in Belgium respond to changes in competitors' prices. We show that remote wages also respond strongly to changes in competitors' wages.

Third, 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). Our paper lies at the intersection of this literature, as the cross-border contracts in our platform can be simultaneously interpreted as trade in services, offshoring, or 'tele-migration'. We complement these papers by showing that in the globalized market for remote work, a worker's wage responds strongly to changes in the wages of foreign competitors.

Fourth, our paper relates to the literature that measures which occupations are easier to offshore. Existing measures hinge on surveys and subjective judgments to classify the offshorability of a job, and tend to consider all jobs that can be done remotely as being easily offshorable (e.g. Blinder 2009, Blinder and Krueger 2013). We contribute to that literature by providing a measure that is based on the prevalence of cross-border contracts, and show that there is substantial heterogeneity in the frequency at which jobs are offshored across occupations that can be done remotely.

Finally, a rapidly growing literature uses data from web-based job platforms to study topical questions in Labor Economics. Horton et al. (2011) highlight the potential of using web-based job platforms for conducting experiments. Horton (2017a), Horton (2017b), and Barach and Horton (2021) use experimental data from a large platform to study how minimum wages, recruiting recommendations, 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. Closer to our paper is Horton et al. (2018), who estimate a gravity equation and document that most contracts in their web-based job platform are cross-border. We contribute to this paper by documenting wage gaps across countries and by providing a measure of offshorability for the multiple detailed occupations in the platform. Finally, in contemporaneous work, Horton (2021) shows that Russian workers increased hours-worked relative to non-Russian workers following the 2014 depreciation of the Ruble, without changing their dollar wages. Relative to that paper, we study exchange rate pass-through into wages more broadly, and also evaluate how remote wages respond to shocks that affect a worker's foreign competitors.

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 provides our measures of job offshorability, and the last section concludes.

2 Data

2.1 Data description

Web-based job platforms are becoming increasingly prominent in the US and the world. These platforms match workers and employers located around the world who buy and sell services that are delivered online. According to the ILO (2021), the number of web-based job platforms tripled over the last decade, generating over 52 billion US$ in 2020.

Our data comes from one of the largest platforms in the market today. The platform has millions of registered workers and employers around the globe that transacted around $2 billion in 2020. Workers in the platform create an online 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. Employers can post job listings, to which workers can apply, or alternatively search for workers that match their needs. The platform encompasses remote jobs from a wide range of industries, ranging from accountants to web developers. Billing and payments are handled by the platform, and jobs are paid within

14 days of completion. The platform sets percentage fees on the worker's earnings, which are based on a sliding scale that depends on lifetime earnings.

Rather than focusing on the millions of registered, and potentially inactive, workers, we base our analysis on a subsample of workers that are active and have experience in the platform. We make use of two sets of data.

2.1.1 Worker-level data

We build our first dataset by collecting data from the publicly-available profiles of workers in the platform. The unit of observation in this dataset is a worker, so we will refer to it as the 'worker-level' data. While there are millions of workers with a profile in the platform, we limit our sample to those with an active profile, positive earnings, and job experience to make sure our analysis is based on workers that are actually using the platform. The worker profiles indicate an 'ask' hourly wage at which the worker is willing to work, and a number of worker-level characteristics that employers can observe when searching for a worker. The dataset contains information on the following characteristics:

General information: The online platform displays the name and location (country and city) of each worker, as well as the type of jobs or 'occupations' that each worker can perform. These 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 availability.

Skills: Workers can list a number of predetermined skills and take online examinations through the platform to certify their expertise in certain areas, such as 'English to Spanish' Translation. We observe about 200 different tests on the platform. We observe which are the tests that each worker has taken, along with the score and rank percentile 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. In particular, the platform reports the total earnings, the total number of jobs, and the total number of hours worked by each worker. The platform also reports the average response time of each worker and the percentage of contracted jobs that the worker has completed (labeled as '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 contracted their first job at least 90 days ago.

We obtained multiple snapshots of the worker-level data. The first (baseline) snapshot was collected in January 2019 and includes information on 100,023 workers that were active in the platform with positive earnings. We have since then collected two additional snapshots, one between October 2020 and February 2021, with updated information on wages for workers in the first snapshot, and another one in March 2021, which includes information on a new set of workers. In the first two snapshots, workers can be listed under multiple occupations. In the last snapshot, workers could only choose one occupation for their profile. We will only use the March 2021 snapshot for our analysis in Section 5.

2.1.2 Job-level data

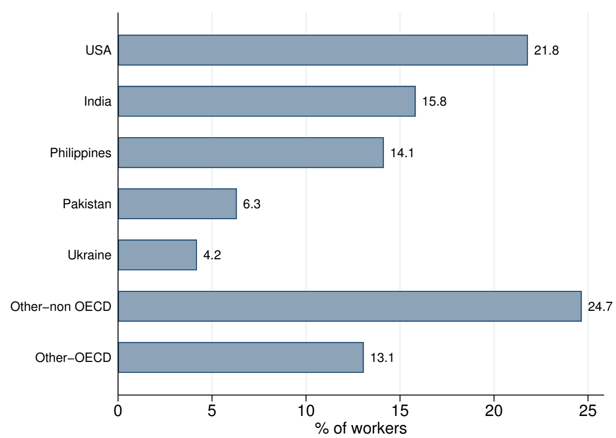
We build our second dataset by scraping the job histories of a subset of 30,520 workers that were present in the January 2019 worker-level dataset. The unit of observation in this dataset is a job or contract, and we will refer to these data as the 'job-level' data. The dataset can be merged with the worker-level dataset using the workers' unique identifiers. For each job that a worker has started, the platform reports a description of the job, the total payment and, if the contract was stipulated on an hourly basis, the hourly rate and number of hours worked. We will refer to this hourly wage as the 'transacted' wage to distinguish it from the 'ask' wage in the workers' profiles. The job-level data also specifies the start date and, if the job is not still in progress, the job's end date. Finally, for a subsample of 348,000 jobs, we were able to obtain information on the employer's identifier and nationality.

2.2 Summary statistics

This section provides summary statistics for the worker-level and the job-level datasets.

Worker-level data: The worker-level data includes 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 27 countries with at least 500 workers, 67 countries with at least 100, and 91 countries with at least 50 workers. Figure 1 shows the distribution of workers across the major countries in the sample. The sample includes both developed and developing countries, though workers are not evenly distributed across the world. The countries with the most workers in our sample are the US, India, Philippines, Pakistan, and Ukraine, which together contain 60% of all workers. Every other country has less than 4% of the workers in the sample. The figure shows that most workers are located in non-OECD countries.

Figure 1: The distribution of workers in the worker-level data

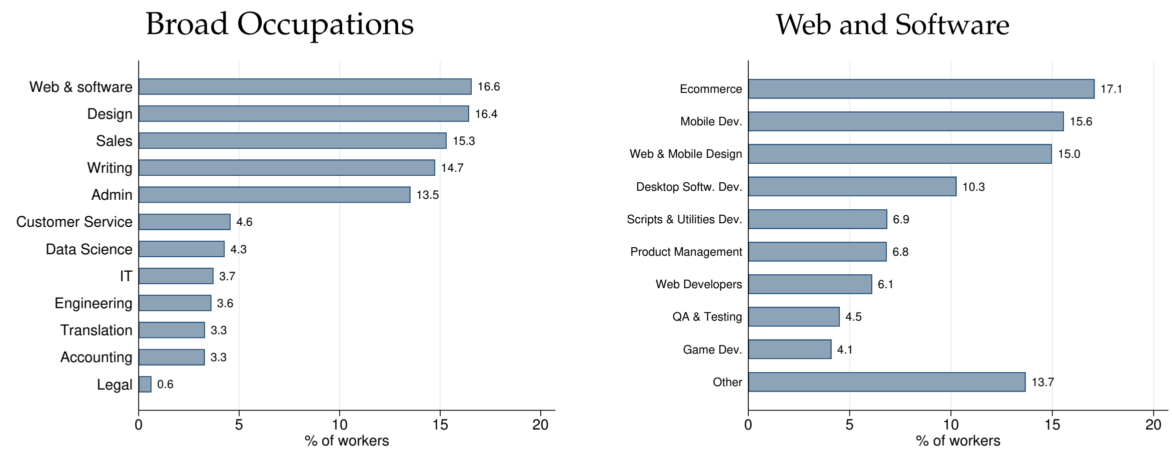


Notes: The figure shows the distribution of workers across countries in the worker-level data.

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

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'.

as large as the mean. The average worker in the data has completed 69 jobs, worked 1,801 hours, 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 income per capita in countries such as India, Pakistan, or 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 to be 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. The degree of heterogeneity can also be inferred from the fact that only 41% of workers are classified as 'Top Rated', and only 28% have a success rate of 100%.

Job-level data: The job-level data contain information for 348,000 jobs performed by a subsample of 30,520 workers, for which we observe the identity and location of the employer. Figure 3 compares the geographical distribution of workers and employers in the data. The distribution of workers is very similar to that in the worker-level data: over 60% of 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

Table 1: Summary statistics: worker-level data

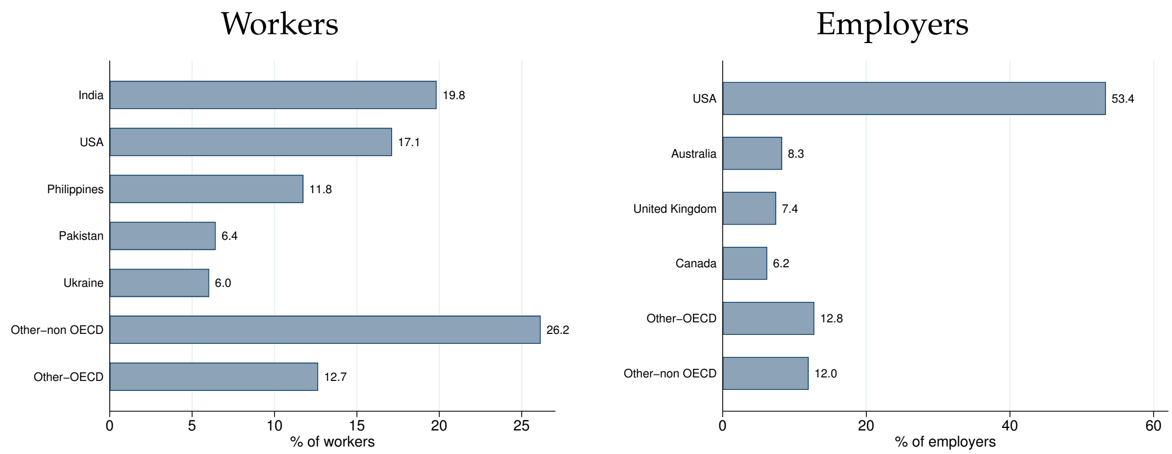
	Mean	Median	St. Dev.	5 pct	95 pct
Hourly wage	25	18	27	5	75
Number of jobs	69	10	642	1	147
Hours worked	1,801	408	3,388	4	8,515
Total earnings	18,667	4,000	62,558	20	90,000
Number of tests	4	3	4	1	10
Average score	4.23	4.25	0.50	3.38	5

	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 table reports summary statistics from the worker-level data. The top of the table reports moments of the distribution of worker characteristics. Hourly wages refers to the ask wage specified in the worker's profile. Number of jobs, hours worked, 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.

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. We will later refer to these jobs as being offshored. Only 24% of the jobs completed by US workers are offshored, while 97% of the jobs completed by non-US workers are offshored. On the flip side, 79% of the jobs contracted by US employers are offshored, while 94% of the jobs contracted by non-US employers are offshored. Thus, non-US workers almost exclusively work for foreign employers, and non-US employers almost exclusively hire foreign workers. In contrast, US workers and employers work with people both in the US and abroad, though US workers work mainly for domestic employers.

Figure 3: 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).

Comparability of ask vs. transacted wages: As noted above, the worker-level data contain information on the hourly ask wage listed on the worker's profile, while the job-level data contain how much workers were actually paid per hour in each job. Figure (A.1) in the Appendix shows a scatter plot of a worker's ask wage in the January 2019 worker-level dataset and the workers' 2018-2019 average hourly wage based on transactions recorded in the job-level dataset. The figure shows a tight relationship between the two. First, the slope of the relationship is 0.91, which means that for an additional dollar in asking wage, workers end up receiving 0.91 dollars in transacted wage. Second, 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 seems to be small.

3 Remote wages and workers' locations

This section documents differences in wages across remote workers located in different regions. We start by documenting wage differences across countries. We first compute average residual wages in each country relative to the US. To do so, we estimate the following OLS regression using the job-level data:

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

Here, w_{fi} is the (log) wage paid by employer f to worker i in a given job. $\mathbb{D}_f$ is a set of country-of-employer fixed effects, and $\mathbb{I}_{i=f}$ is an indicator that is equal to one if the employer and worker are in the same country. $\mathbb{S}_i$ is the full set of occupation fixed effects. 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), and an indicator for whether the worker works in an agency (multi-worker or single worker). Finally, $\mathbb{C}_i$ is the full set of fixed effects for the workers' countries. The omitted country category is the US, so these fixed effects measure average wages of workers in each country relative to the average wage of workers in the US. The results from this regression are reported in Appendix Table A4, which shows that remote wages are positively related to our measures of experience, skills, and quality ratings.

Table 2 evaluate how wages vary within and across countries by conducting a variance decomposition of equation (1). It shows that the variance in a worker's country of origin accounts for 23% of the dispersion of wages, and the covariance between the country of origin and other observables accounts for an additional 15%. This is more than the variance accounted for by all the other controls in equation (1).[6]

Table 2: Variance decomposition of wages

Var(country)	Var(controls)	2 x Cov(country,controls)	Var(residual)
0.23	0.17	0.15	0.45

Notes: The Table reports the variance decomposition of equation (A4) using transacted wages from the job-level data.

Figure 4 compares the relative wages to the relative GDP per capita of each of the 67 countries with at least 100 workers in our sample.[7] Panel (a) plots the average log wage in each country relative to the US. Panel (b) plots the average residualized relative wage estimated with the fixed effects $\mathbb{C}_i$ in equation (1). Both figures show a very strong and positive relationship between relative wages and GDP per capita: workers from richer countries earn on average higher wages. The slope of this relationship is 0.23 (SE 0.034) in Panel (a) and 0.22 (SE 0.025) in Panel (b), and the R^2 are is 0.47 and 0.59, respectively. It is worth noting that the estimation in Panel (b) also controls for country-of-employer

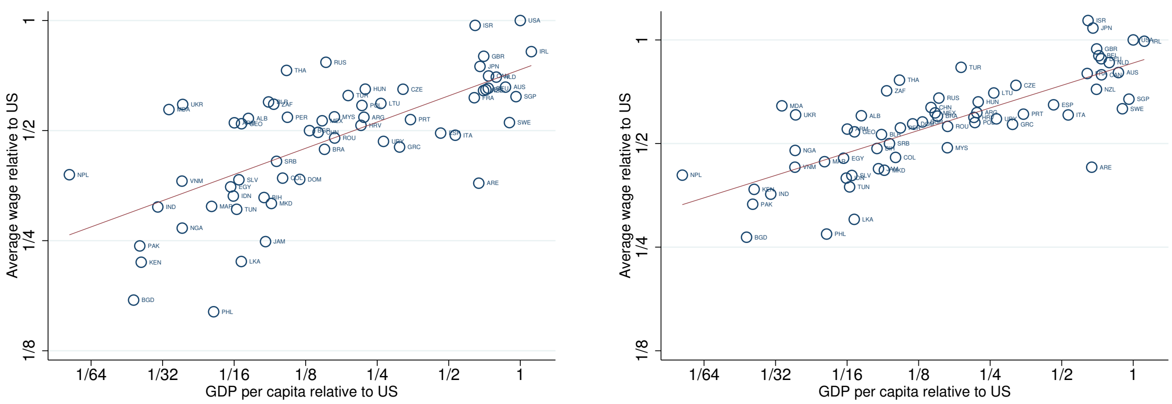
[6]A regression of log-wages on the set of country fixed effects $\mathbb{C}_i$ has an R^2 of 0.41. This is economically large since the R^2 of estimating equation (1) with all the additional controls is 59%.

[7]Appendix Figure A.2 shows similar results when using the larger sample of workers with available ask wage data.

fixed effects. Hence, the observed variation arises from differences in wages paid by employers from the same country. The comparison between Panels (a) and (b) reveals that cross-country differences in average wages are not driven by observable worker characteristics nor by differences in the location of the employers. 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) Raw data (b) Residual wages



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) plots the average ask wage in each country relative to the US. Panel (b) reports the average residualized wage in each country relative to the US obtained from the country fixed effects estimated in equation (1) with the job-level data. The red lines show the linear fit of the data. The estimated slope is 0.23 (0.034) in panel (a) and 0.22 (0.025) in panel (b), and the R^2 are 0.47 and 0.59, respectively.

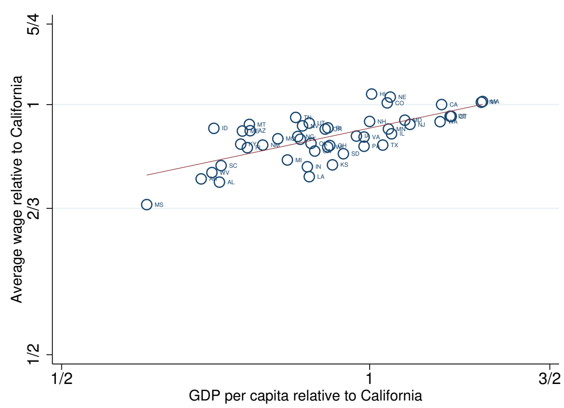
Wage differences across US states: We now document differences in remote wages across workers located in different US states. We follow the strategy in the previous section and first compute average wages in each state after residualizing them for worker characteristics. Unfortunately, the job level data does not have enough workers in each of the US states to precisely estimate average residual wages at the state level (there are only 12 states with more than 100 workers). Thus, we estimate the equation using the worker-level data, where the unit of observation is a worker. With that in mind, we estimate the following OLS regression using the worker-level data:

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

where now $\mathbb{C}_i$ is the full set of fixed effects for the workers' state-of-origin. 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 worker-level data, we cannot control for the location of the employers.

Figure 5 compares the relative wages to the relative GDP per capita of each of the 47 states with at least 30 workers in our sample.[8] 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^2 is 0.48. These patterns are remarkably similar to the cross-country patterns documented above. Wage differences across countries and US states suggest that while remote jobs do not require the worker to be present at a specific location, the worker's location plays a large role in shaping remote wages.

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



Notes: The x-axes report 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) with the worker-level data. The red lines show 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 differences

Decomposing wage differentials: The previous results show that wage differences across countries cannot be explained by differences in average worker characteristics, occupa-

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

tional composition, or the location of employers hiring workers in the platform. In Appendix A.2, we further document this fact by conducting a 'Blinder-Oaxaca' decomposition. The goal of this decomposition is to quantify the extent to which cross-country wages differences are driven by cross-country differences in workers' skills or by differences in returns to skills across countries—i.e., from the perspective of equation (2), are wage differences driven by differences in average $\boldsymbol{X_i}$ or in $\boldsymbol{\beta}$? We find that differences in worker characteristics across countries are not strongly correlated with cross-country differences in GDP per capita. Thus, differences in returns are the main drivers of wage differences with the US.

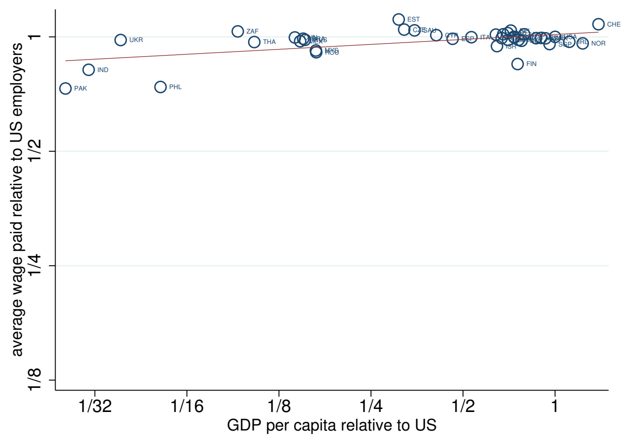
Pricing to market: Finally, we evaluate whether workers price to market, that is, whether the wage earned by a worker depends on the employer's location. With this in mind, we estimate the following regression using the job-level data

$$w_{fi} = \mathbb{W}_i + \mathbb{D}_f + \mathbb{I}_{i=f} + \varepsilon_{fi}. \tag{3}$$

The regression includes worker fixed effects $\mathbb{W}_i$, country-of-employer fixed effects $\mathbb{D}_f$, and an indicator variable that is equal to one if the employer and the worker are from the same country. The omitted country for the employer fixed effects is the US, so the country fixed effects measure average wages paid by employers in each country relative to average wages paid by employers in the US. Since the regression includes worker fixed effects, this coefficient is estimated from variation in wages received from different employers of a given worker.

Figure 6 plots differences in employers' country fixed effects against relative GDP per capita of the employer's country for the set of countries that have more than 100 employers. It figure shows that workers price discriminate across countries: they get paid more when working for employers from richer countries. The slope of this relationship is 0.06, with a standard error of 0.02 and an R^2 of 0.3. For example, employers in the two poorest countries in our sample (Pakistan and India) pay 42% and 29% less than employers in the US for the services of the same worker. We note, however, that the magnitude of this relationship cannot account for the wage differentials documented in the previous section, both because the degree of pricing to market is small relative to the differences in wages depicted in Figure 4, and because workers in both rich and poor countries tend to work mainly for employers located in rich countries (see Figure 3).

Figure 6: Wages paid by employers from different countries and GDP per capita



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 reports the set of country-of-employer fixed effects $\mathbb{D}_z$ (relative to employers in the US) estimated according to equation (3). The red line reports the linear prediction, and has a slope of 0.06 (0.02), and an R^2 of 0.30.

4 Remote wages and international shocks

This section studies how remote wages are affected by international shocks. We start by laying down a simple model of equilibrium wage determination motivated by the findings from the previous section to guide our analysis.

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:

$$Y_t = \left[\sum_j Y_{jt}^{\frac{\eta-1}{\eta}}\right]^{\frac{\eta}{\eta-1}}, \tag{4}$$

where Y_{jt} denotes production from sector j, which is determined by

$$Y_{jt} = \left[\sum_c A_{jct}^{\frac{1}{\rho}} L_{jct}^{\frac{\rho-1}{\rho}} \right]^{\frac{\rho}{\rho-1}}. \tag{5}$$

Here, L_{jct} denotes the efficiency units of labor from location c in sector j, A_{jct} 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 $\rho < \infty$.

Let Ω_{jct} denote the dollar wage per efficiency unit of labor from location c in sector j. Cost minimization implies that the demand for labor is given by

$$L_{jct} = A_{jct} \left[\frac{\Omega_{jct}}{P_{jt}} \right]^{-\rho} Y_{jt}, \tag{6}$$

and that the unit cost of production in sector j is

$$P_{jt} = \left[\sum_c A_{jct} \Omega_{jct}^{1-\rho} \right]^{\frac{1}{1-\rho}}, \tag{7}$$

with costs shares given by $s_{jct} \equiv \frac{\Omega_{jct} L_{jct}}{P_{jt} Y_{jt}} = \frac{A_{jct} \Omega_{jct}^{1-\rho}}{\sum_c A_{jct} \Omega_{jct}^{1-\rho}}$.

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_{ijt} 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 $Z_{ijt} \times B_{jct}/H_{ij}$, where B_{jct} is the wage per efficiency unit of labor in the local labor market, and H_{ij} 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.[9] 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

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

exists a cutoff cost for working in the local labor market given by

$$H_{ij} \geq \underline{H}_{jct} \equiv B_{jct}/\Omega_{jct}, \tag{8}$$

such that workers with H_{ij} above this cutoff choose to work remotely. We assume that Z_{ijt} and H_{ij} are independently distributed and that the distribution of H is $f(H) = \frac{\theta\kappa_{jc}^{\theta}}{H^{1+\theta}}$ with support $[\kappa_{jc}, \infty)$. Let N_{jct} denote the number of workers in location c. Then, the supply of remote labor in sector j from location c is given by

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

where $Z_{jct} \equiv \mathbb{E}_c\left[Z_{ijt}\right]$ denotes the average efficiency units of labor of workers from location c in sector j, and $\tilde{N}_{jct} \equiv N_{jct} Z_{jct} \kappa_{jc}^{\theta}$ collects supply shifters other than B_{jct}. Equation (9) states that the labor supply elasticity is given θ.

Equilibrium: Combining the demand functions associated with (5), equations (6), (9), and using a lowercase to denote variables in logs, we obtain the equilibrium wage per efficiency unit of remote labor for sector j in location c:

$$\omega_{jct} = \frac{\theta}{\rho+\theta} b_{jct} + \frac{\rho-\eta}{\rho+\theta} p_{jt} + \frac{1}{\rho+\theta} \varphi_{jct} + \frac{1}{\rho+\theta} \phi_t, \tag{10}$$

where $\varphi_{jct} \equiv a_{jct} - \tilde{n}_{jct}$ collects the location-sector-specific supply and demand shifters, and $\phi_t \equiv \eta p_t + y_t$, where p_t denotes the log price of the final good.

Remote wages and workers' locations: We now evaluate wage differences across remote workers. Let $w_{ijt} \equiv \omega_{jct} + z_{ijt}$ 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,

$$w_{ijt} = \frac{\theta}{\rho+\theta} b_{jct} + \frac{\rho-\eta}{\rho+\theta} p_{jt} + \frac{1}{\rho+\theta} \varphi_{jct} + \frac{1}{\rho+\theta} \phi_t + z_{ijt}. \tag{11}$$

Equation (11) states that wage differences across workers in the same sector can arise from differences in local wages, b_{jct}, location-specific demand and supply shifters, φ_{jct}, and workers' efficiency units, z_{ijt}. 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_{ijt}. If instead, labor supply is close to being perfectly elastic, $\theta \to \infty$, wage differences are given by differences in local wages b_{jct} and differences in z_{ijt}. For finite values of ρ and θ, the elasticity of remote wages with respect to local wages is positive but less than one, $\frac{\theta}{\rho+\theta} < 1$.

We can use equation (11) to interpret the results from Section 3. If local wages can be proxied by the GDP per capita in a location, equation (11) suggest 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 (11) are uncorrelated with GDP per capita, then the evidence from Section 3 suggests that $\frac{\theta}{\rho+\theta} \simeq 0.2$. However, note that even if $\theta = 0$, a positive correlation between wages and GDP per capita can arise from systematic differences in φ_{jct}, or if our controls in equation (2) do not properly account for differences in workers' efficiency units z_{ijt} that are correlated with differences in GDP per capita. The following section uses time variation in wages to unpack these alternative interpretations.

Wage changes: We now evaluate the model's predictions for wage changes. Since we do not observe changes in local wages at short frequencies, we make the approximation:

$$db_{jct} \simeq \gamma_{jct} + \pi_{ct} + de_{ct}, \tag{12}$$

where γ_{jct} 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.

Let $dx_{jt} \equiv \sum s_{jct} dx_{ct}$ denote the (sector-specific) cross-country average change in a variable, with weights corresponding to a country's cost-share in a sector. Differentiating equations (7) and (11) and substituting yields:[10]

$$dw_{ijt} = \frac{\theta}{\rho+\theta}\left[de_{ct} + \pi_{ct}\right] + \frac{\rho-\eta}{\rho+\theta} dw_{jt} + d\psi_{jct} + d\psi_{jt} + d\psi_t + dz_{ijt}, \tag{13}$$

and

$$dw_{jt} \equiv \sum_c s_{jct} \mathbb{E}_c \left[dw_{ijt}\right] = \frac{\theta}{\theta+\eta}\left[de_{jt} + \pi_{jt}\right] + d\phi_{jt} + d\phi_t. \tag{14}$$

Here, dw_{jt} is an index of wage changes in the remote market, $d\psi_{jct} \equiv \frac{1}{\rho+\theta}\left[d\varphi_{jct} + \theta\gamma_{jct}\right]$ collects location-sector-specific supply and demand shifters, $d\psi_{jt} \equiv \frac{\rho-\eta}{\rho+\theta}\left[\frac{1}{1-\rho} da_{jt} - dz_{jt}\right]$ and $d\phi_{jt} \equiv \frac{1}{\theta+\eta}\left[\theta\gamma_{jct} + d\varphi_{jt} + \frac{\rho-\eta}{1-\rho} da_{jt}\right] + dz_{jt}$ collect sector-specific shifters, and $d\psi_t \equiv$

[10] See Appendix A.3 for a derivation.

$[\rho + \theta] \, d\phi_t$ is an aggregate shifter.

Equations (13) and (14) 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 the job-level dataset to estimate how wages respond to international shocks.

4.2.1 Preliminaries

The job-level dataset covers a sample of 641,679 jobs performed between January 2012 and April 2020. As noted in Section 2, for each job in the data, we observe the start date, the total payment, and the worker's id 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 the jobs' descriptions using a machine-learning algorithm.[11]

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).[12] The start date of the job is reported at a monthly frequency, though a worker can start multiple jobs on the same month. We collapse the data at the monthly level so that the unit of observation is a worker-sector-month.

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 $\Delta_s w_{ijt} \equiv w_{ijt} - w_{ijt-s}$ 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 Table A3 and Figure A.3 in the Appendix A.1. In

[11] 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'.

[12] 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.

the following analysis, we use 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 (13). Note that $\Delta_s w_{jt}$ varies across time spells and sectors, so that we can estimate equation (13) as:

$$\Delta_s w_{ijt} = \beta_1 \Delta_s e_{ct} + \beta_2 \pi_{ct_s} + \mathbb{C} \times \mathbb{J} \times s + \mathbb{T}_{jt_s} + \epsilon_{ijt_s}. \tag{15}$$

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_{jct}. $\mathbb{T}_{jt_s}$ is a set of fixed effects for each sector-time-spell that controls for changes in w_{jt} and for the aggregate and sector-specific shifters ψ_{jt} and ψ_t. The error term is given by $\epsilon_{ijt_s} \equiv \Delta_s \tilde{z}_{ijt} + \Delta_s d\tilde{\psi}_{jct}$, where the notation $\tilde{x}$ denotes the deviation of a variable from the sector-time-spell average and its country trend. Equation (15) 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 (15) 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. $cov(\Delta_s \tilde{z}_{ijt} + \Delta_s \tilde{\psi}_{jct}, \Delta_s e_{ct}) = 0$. This exclusion restriction requires changes in exchange rates to be uncorrelated to trend deviations in sectoral productivities 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.[13] 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 (13), wages respond to changes in competitors' wages with an elasticity $\frac{\rho-\eta}{\rho+\theta}$. We cannot test this implication using equation (15), since $\Delta_s w_{jt}$ is absorbed by the fixed-effects $\mathbb{T}_{jt_s}$. To test this implication directly, we estimate the following equation:

$$\Delta_s w_{ijt} = \beta_1 \Delta_s e_{ct} + \beta_2 \pi_{ct_s} + \beta_3 \Delta_s w_{jt} + \mathbb{C} \times \mathbb{J} \times s + \mathbb{T}_{t_s} + \varepsilon_{ijt_s}, \tag{16}$$

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

where $\epsilon_{ijt_s} \equiv \Delta_s \hat{z}_{ijt} + \Delta_s \hat{\psi}_{jct} + \Delta_s \hat{\psi}_{jt}$, and $\hat{x}$ denotes the deviation of a variable from the time-spell average and the country-sector trend. The OLS estimates of (16) are inconsistent if $\Delta_s w_{jt}$ is correlated with ε_{ijt_s}, which would be the case if the detrended aggregate shifters $\Delta_s \hat{\phi}_{jt}$ and $\Delta_s \hat{\psi}_{jt}$ are correlated. We thus pursue an IV approach. From equation (14), a natural instrument for $\Delta_s w_{jt}$ is

$$\Delta_s \Theta_{jt} \equiv \pi_{jt_s} + \Delta_s e_{jt}, \tag{17}$$

which correlates with $\Delta_s w_{jt}$ but is orthogonal to ε_{ijt_s} under the exclusion restriction.

Measuring changes in competitors' wages: To implement equation (16), we need to construct an index of average wage changes in each sector, $\Delta_s w_{jt} \equiv \sum_c s_{cjt} \mathbb{E}_c \left[\Delta_s w_{ijt} \right]$. 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 $\Delta_s w_{ijt}$ is not observed for many workers.

With this in mind, we approximate $\Delta_s w_{jt}$ 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

$$w_{ijt} = \delta_{ji} + \delta_{jt} + v_{ijt},$$

where δ_{ji} and δ_{jt} 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., $\Delta_s w_{jt} = \Delta_s \delta_{jt}$.[14] Finally, in building the instrument in (17), we proxy s_{cjt} by the share of jobs performed by workers from country c in sector j throughout our sample. Figure A.4 in the Appendix reports the variation in s_{cjt} across sectors.

[14] This procedure recovers up to a first order approximation the time series of dw_{jt}. To see this, note that from equations (13) and (14) we have:

$$\begin{aligned} d\delta_{jt} &= \frac{\theta}{\rho+\theta}\left[de_t + \pi_t\right] + \frac{1}{\rho+\theta}\left[d\varphi_{jt} + \theta\gamma_{jt}\right] + \frac{\theta+\eta}{\rho+\theta} dz_{jt} + \frac{\rho-\eta}{\rho+\theta}\frac{1}{1-\rho} da_{jt} + \frac{\rho-\eta}{\rho+\theta} dw_{jt} \\ &= \frac{\theta+\eta}{\rho+\theta} dw_{jt} + \frac{\rho-\eta}{\rho+\theta} dw_{jt} = dw_{jt}. \end{aligned}$$

4.2.4 Results

We present our estimates in Table 3. Column 1 shows the results from estimating equation (15) by OLS, which in addition to $\Delta_s e_{ct}$ and π_{c,t_s} includes country-sector-specific trends and sector-time-spell fixed effects. We cluster standard errors at the time-spell and country level. The estimated partial pass-through is elasticity is $\hat{\beta}_1 = 0.138$ 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 0.86). The coefficient on inflation is similar, $\hat{\beta}_2 = 0.133$, though we cannot reject the null hypothesis that it is equal to zero. In addition, we cannot reject the null that $\beta_1 = \beta_2$.

Column 2 shows the results from estimating equation (16) by OLS, which controls for country-sector-specific linear trends and time-spell fixed effects but includes $\Delta_s w_{jt}$ instead of the sector-time-spell fixed effects $\mathbb{T}_{jt_s}$. Standard errors are clustered at the 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 $\hat{\beta}_1 = 0.154$ and $\hat{\beta}_2 = 0.177$. The coefficient on the aggregate wage index is $\hat{\beta}_3 = 0.653$ and statistically different from zero.

Column 3 reports the 2SLS estimates in which we use π_{jt_s} and $\Delta_s e_{jt}$ separately as instruments for $\Delta_s w_{jt}$. The estimated coefficient on the exchange rates and inflation are almost identical to those in Column 2. More importantly, the coefficient on $\Delta_s w_{jt}$ is 0.954, and is statistically significant at the 1% level. The bottom of Table 3 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 π_{jt_s} and $\Delta_s e_{jt}$ are statistically significant and both contribute to the variation in $\Delta_s w_t$. 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 $0.954 \times \left[s_{c'j} \times 1\%\right]$. Finally, Column 4 reports the reduced-form estimates behind equation (16). The wages of workers respond to average changes in the exchange rate and inflation in their competitors' countries, with statistically significant elasticities of 0.053 and 0.587, respectively.[15]

[15] Table A5 in the Appendix reports the results obtained after imposing the constraint $\beta_1 = \beta_2$.

Table 3: Wage changes and international shocks

	(1)	(2)	(3)	(4)
	$\Delta_s w_{ijt}$	$\Delta_s w_{ijt}$	$\Delta_s w_{ijt}$	$\Delta_s w_{ijt}$
$\Delta_s e_{ct}$	0.138**	0.154**	0.149**	0.165**
	(0.061)	(0.064)	(0.063)	(0.069)
π_{c,t_s}	0.133	0.177*	0.184*	0.136
	(0.112)	(0.105)	(0.101)	(0.120)
$\Delta_s w_{jt}$		0.653***	0.954***	
		(0.057)	(0.077)	
$\Delta_s e_{jt}$				0.053***
				(0.007)
π_{j,t_s}				0.587***
				(0.057)
Observations	109669	109669	109669	109669
R-squared	0.00015	0.0060	0.0047	0.0030
Test $\beta_1 = \beta_2$	0.96	0.81	0.70	0.024
Specification	OLS	OLS	2SLS	OLS
F stat 1st stage			223.2	

Notes: The table reports the results from estimating equations (15) and (16). All columns include country-sector-specific linear trends. Standard errors are clustered at the 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 towards zero. In fact, Appendix Figure A3 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 1 in Appendix Table A7 reports the results. The coefficient on the change in the domestic exchange rate in increases from the baseline value of 0.149 to 0.166, and the coefficient in domestic inflation increases from 0.184 to 0.224. 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 $\Delta_s w_t$ is by definition a function of each worker's wage, and is thus correlated with the error term in equation (13). 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 (13) using the leave-one-out index for the competitors' wages, $\Delta_s w_{-ijt} \equiv \sum_{l \neq i} \frac{s_{ljt}}{1-s_{ijt}} \Delta_s w_{ljt} = \left[\Delta_s w_{jt} - s_{ijt} \Delta_s w_{ijt}\right] / \left[1 - s_{ijt}\right]$, where s_{ijt} is the market share of worker i in sector j.[16] Note also that if all workers have small market shares $s_{ijt} \to 0$ (as they do in practice), then $\Delta_s w_{-ijt} \to \Delta_s w_{jt}$. The results of this alternative estimation are presented in Column 2 of Appendix Table A7, and coincide with our baseline estimation.

Placebo analysis: To validate our 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 assign to each job it's least likely sector in the following way. Our machine-learning algorithm classified jobs into four broad sectors using the jobs' descriptions. For each job, the algorithm estimates the likelihood across 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 'least likely sector' to each job, which is given be the sector with the lowest estimated likelihood. We the extend the estimating equation (16) to include the average wage change of a job's least likely sector as an additional regressor.

[16] Note that equation (13) can also be written as

$$dw_{ijt} = \frac{\theta}{\tilde{\rho}_{it} + \theta + s_{ijt}\eta}\left[de_{ct} + \pi_{ct}\right] + \frac{\tilde{\rho}_{ijt} - \eta\left[1 - s_{ijt}\right]}{\tilde{\rho}_{ijt} + \theta + s_{ijt}\eta} dw_{-ijt} + \frac{d\psi_{jct} + d\psi_{jt} + d\psi_t + dz_{ijt}}{\tilde{\rho}_{ijt} + \theta + s_{ijt}\eta}, \tag{18}$$

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

Column 3 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 coefficient on the wage changes of the least likely competitors is much smaller in absolute value and has the opposite sign.

Alternative assumptions on country-trends: Colums 4 and 5 in Appendix Table A7 reestimates equations (15) and (16) using alternative controls for the country-specific trends. Columns 4 does not control for country-sector-specific trends. Columns 5 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: In this section, we reestimate partial ERPT elasticities using the worker-level data. 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-February 2019 and once in October-November 2019. Workers are listed across (possibly more than one of) the 91 occupations in the platform described in Table A1 in the Appendix.[17] In this case, we can estimate the partial pass-through elasticities from equation

$$\Delta w_{ij} = b_1 \Delta e_c + b_2 \pi_c + \mathbb{S}^j + \mu_{ij}, \tag{19}$$

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 have one observation per worker. Equation (19) is the worker-level data analog to (15). Here, the coefficients $b_1 = b_2 = \frac{\theta}{\rho+\theta}$ are identified from the country variation in exchange rates and inflation. An important difference 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 Appendix Table A7 Column 6 and 7. 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 even smaller than those estimated with the job data, reinforcing our conclusion that there is low pass-through into dollar wages. This

[17] An additional benefit of analyzing the ask wages in the worker-level data is that it reduces selection concerns that may arise in our analysis of transacted wages. In the following analysis, selection is not a concern since we analyze the response of ask wages of all workers, including those that do not end up being hired.

occurs in part because there is a large fraction of ask wages that do not change from one period to the next. 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 presents measures of the frequency with which jobs from different occupations are offshored. While existing measures of job offshorability typically hinge on subjective judgments on 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. We present evidence on the relationship between the prevalence of job offshoring and the cross-country wage dispersion within an occupation.

5.1 Measurement

For a subset of jobs in the job-level data, we observe the location of both the worker and the employer. 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 probability that a US employer chooses to offshore a contract in that occupation. With this in mind, we assign the jobs in the job-level data to occupations listed in the worker's profile. For each of the 91 detailed occupations in the worker-level data, we compute the share of US jobs performed by non-US workers:

$$\mathcal{O}^j = \frac{\text{jobs in } j \text{ where cty. employer=US and cty. worker}\neq\text{US}}{\text{All jobs in } j \text{ where cty. employer=US}}. \tag{20}$$

Our measure $\mathcal{O}^j$ captures the prevalence of offshored contracts in an occupation in the US. In contrast, previous measures in the literature often capture the extent to which a job can be performed remotely rather than whether the job can be offshored. We highlight that some jobs that can be done remotely are hard to offshore. As we will see below, while all jobs in our data are being performed remotely, there is substantial variation among which jobs are offshored.

5.2 Results

Table 4 reports our measure for the most and least frequently offshored occupations categories 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 30-40% of grant writers jobs are offshored, even though all of them are performed remotely. In fact, there is substantial heterogeneity across occupations. For example, Interior Design 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.

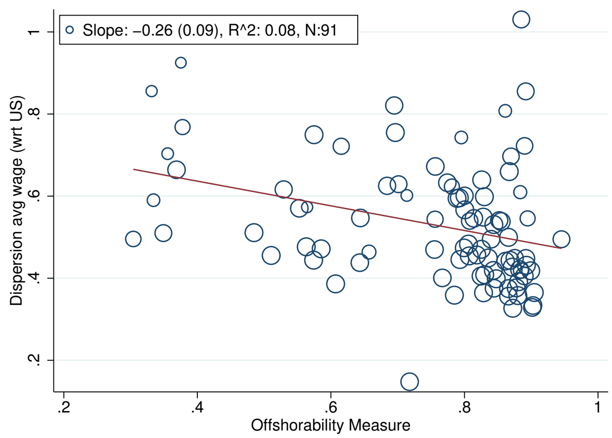
Table 4: Most and least offshored occupations

Most offshored		Least offshored	
ERP / CRM Specialists	0.95	Grant Writers	0.30
Mobile Developers	0.90	Corporate Law	0.33
Interior Designers	0.90	Contract Law	0.33
Medical Translators	0.90	Resumes & Cover Letters Writers	0.35
Motion Graphics	0.89	Paralegal	0.36

Notes: The Table reports the measure defined in equation (20) for the Top 5 and Bottom 5 occupations.

Offshoring and wage dispersion: Figure 7 plots our measure (x-axis) and the 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 result provides direct evidence that offshoring can play an important role in equalizing remote wages across countries, even though the differences remain large today.

Figure 7: Offshoring and wage dispersion

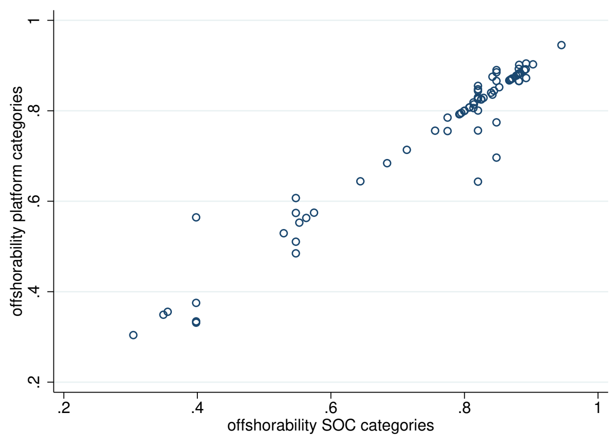


Notes: Each circle represents an occupation. The figures compares the measure in equations (20) to the dispersion in average wages across countries in each occupation. Circle sizes represent the number of countries with workers in the occupation.

Offshoring across categories in the SOC system: The occupation categories used so far are specific to the platform and differ from those in the Standard Occupational Classification (SOC) system used by the BLS. To make our measure easier to use in future research, we compute offshorability measures for the SOC categories represented in our data. To do so, we manually match the SOC categories to the occupations in the platform using the corresponding descriptions. We compute the offshoring measure of each SOC category based on the two procedures described above. Appendix Table A.1 lists the concordance between the occupation categories in the platform and the SOC, along with the corresponding offshoring measures.

Figure 8 plots the measure 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 (see Appendix Table A.1), 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 offshorability. 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 that a difference of 20% in the probability of offshoring jobs between 'Ecommerce Programmers and Developers' and 'Ecommerce Programmers and Developers' ($\mathcal{O}^j = 0.64$ and $\mathcal{O}^j = 0.85$, 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 8: Offshoring within SOC categories



Notes: Each circle represents an occupation. The figure compares the frequency with which jobs are offshored using equation (20) for SOC categories vs. platform categories.

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, nor by differences in the employers' locations. We also document that remote wages in local currency move almost one-for-one 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 easier to offshore 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, our offshorability measure highlights the fact that whether a job is performed remotely is an imperfect proxy for whether a job can be easily offshored. Future work on how to measure offshorability should take this into account.

References

Amiti, Mary, Oleg Itskhoki, and Jozef Konings, "International shocks, variable markups, and domestic prices," *The Review of Economic Studies*, 2018.

Ashenfelter, Orley, "Comparing Real Wage Rates: Presidential Address," *American Economic Review*, April 2012, *102* (2), 617–42.

Autor, David H., David Dorn, and Gordon H. Hanson, "The China Syndrome: Local Labor Market Effects of Import Competition in the United States," *American Economic Review*, 2013, *103* (6), 2121–2168.

Autor, David H, David Dorn, and Gordon H Hanson, "The China shock: Learning from labor-market adjustment to large changes in trade," *Annual Review of Economics*, 2016, *8*, 205–240.

Baldwin, Richard, *The Great Convergence: Information Technology and the New Globalization*, Harvard University Press, 2016.

_ , *The Globotics Upheaval: Globalization, Robotics, and the Future of Work*, Oxford University Press, 2019.

Barach, Moshe A. and John J. Horton, "How Do Employers Use Compensation History? Evidence from a Field Experiment," *Journal of Labor Economics*, 2021, *39* (1), 193–218.

Blinder, Alan S, "Wage discrimination: reduced form and structural estimates," *Journal of Human resources*, 1973, pp. 436–455.

Blinder, Alan S., "How Many US Jobs Might be Offshorable?," *World Economics*, April 2009, *10* (2), 41–78.

_ **and Alan B. Krueger**, "Alternative Measures of Offshorability: A Survey Approach," *Journal of Labor Economics*, 2013, *31* (S1), 97–128.

Borjas, George J., *Inmigration Economics*, Harvard University Press, 2014.

Burstein, Ariel T. and Gita Gopinath, "International Prices and Exchange Rates," in Kenneth Rogoff Elhanan Helpman and Gita Gopinath, eds., *Handbook of International Economics*, Vol. 4, Elsevier, 2015, chapter 7, pp. 391 – 451.

Card, David and Giovanni Peri, "Immigration Economics by George J. Borjas: A Review Essay," *Journal of Economic Literature*, December 2016, *54* (4), 1333–49.

Cavallo, Alberto, Brent Neiman, and Roberto Rigobon, "Currency Unions, Product Introductions, and the Real Exchange Rate," *The Quarterly Journal of Economics*, 2014, *129* (2), 529–595.

_ , W. Erwin Diewert, Robert C. Feenstra, Robert Inklaar, and Marcel P. Timmer, "Using Online Prices for Measuring Real Consumption across Countries," *AEA Papers and Proceedings*, May 2018, *108*, 483–487.

Dube, Arindrajit, Jeff Jacobs, Suresh Naidu, and Siddharth Suri, "Monopsony in Online Labor Markets," *American Economic Review: Insights*, March 2020, *2* (1).

Feenstra, Robert C. and Gordon H. Hanson, "Global Production Sharing and Rising Inequality: A Survey of Trade and Wages," in "Handbook of International Trade," John Wiley and Sons, Ltd, 2003, chapter 6, pp. 146–185.

Feenstra, Robert C, Robert Inklaar, and Marcel P Timmer, "The next generation of the Penn World Table," *American economic review*, 2015, *105* (10), 3150–82.

Goldberg, Pinelopi Koujianou and Nina Pavcnik, "Distributional Effects of Globalization in Developing Countries," *Journal of Economic Literature*, March 2007, *45* (1), 39–82.

Gopinath, Gita, Emine Boz, Camila Casas, Federico J Díez, Pierre-Olivier Gourinchas, and Mikkel Plagborg-Møller, "Dominant currency paradigm," *American Economic Review*, 2020, *110* (3), 677–719.

_ , Oleg Itskhoki, and Roberto Rigobon, "Currency choice and exchange rate pass-through," *American Economic Review*, 2010, *100* (1), 304–36.

Gorodnichenko, Yuriy and Oleksandr Talavera, "Price Setting in Online Markets: Basic Facts, International Comparisons, and Cross-Border Integration," *American Economic Review*, January 2017, *107* (1), 249–282.

Hjort, Jonas, Xuan Li, and Heather Sarsons, "Across-Country Wage Compression in Multinationals," Working Papers May 2019.

Horton, John, "Price Floors and Employer Preferences: Evidence from a Minimum Wage Experiment," CESifo Working Paper Series 6548, CESifo 2017.

Horton, John J., "The Effects of Algorithmic Labor Market Recommendations: Evidence from a Field Experiment," *Journal of Labor Economics*, 2017, *35* (2), 345–385.

Horton, John J, "The Ruble Collapse in an Online Marketplace: Some Lessons for Market Designers," Working Paper 28702, National Bureau of Economic Research April 2021.

Horton, John J., D.G. Rand, and R.J. Zeckhauser, "The online laboratory: conducting experiments in a real labor market," *Experimental Economics*, 2011, *14*, 399–425.

Horton, John, William R. Kerr, and Christopher Stanton, "3. Digital Labor Markets and Global Talent Flows," in Gordon H. Hanson, William R. Kerr, and Sarah Turner, eds., *High-Skilled Migration to the United States and Its Economic Consequences*, University of Chicago Press, 2018, pp. 71–108.

Hummels, David, Rasmus Jørgensen, Jakob Munch, and Chong Xiang, "The wage effects of offshoring: Evidence from Danish matched worker-firm data," *American Economic Review*, 2014, *104* (6), 1597–1629.

ILO, "The role of digital labour platforms in transforming the world of work," World Employment and Social Outlook 2021, World Employment and Social Outlook 2021.

Itskhoki, Oleg and Dmitry Mukhin, "Exchange Rate Disconnect in General Equilibrium," NBER Working Papers 23401, National Bureau of Economic Research, Inc May 2017.

Oaxaca, Ronald, "Male-female wage differentials in urban labor markets," *International economic review*, 1973, pp. 693–709.

OECD, *Implications of Remote Working Adoption on Place Based Policies* 2021.

Stanton, Christopher T. and Catherine Thomas, "Landing the First Job: The Value of Intermediaries in Online Hiring," *The Review of Economic Studies*, 09 2015, *83* (2), 810–854.

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 A2: (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 A3: Frequency of transacted wage changes

Sample	Freq. Wage Changes	Share Wage Increases	Med. Wage Increase	Med. Wage Decrease
All	0.76	0.64	0.26	-0.22
$\Delta T = 1$	0.70	0.59	0.22	-0.22
$\Delta T \leq med(\Delta T)$	0.71	0.60	0.22	-0.22
$\Delta T > med(\Delta T)$	0.81	0.67	0.29	-0.22

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

Table A4: Wage determinants

	Coef.	Std. Err.			Coef.	Std. Err.
Experience				**Quality ratings**		
Earnings (in logs)	0.057***	(0.001)		Top rated	0.312***	(0.005)
<=5 jobs	0.016***	(0.004)		SR <70%	-0.119***	(0.014)
[6,15) jobs	0.069***	(0.006)		SR [70%,80%)	-0.066***	(0.011)
[15,50) jobs	0.077***	(0.009)		SR [80%,90%)	-0.021***	(0.007)
>=50 jobs	0.086***	(0.021)		SR [90%,95%)	0.015*	(0.008)
Part time/full time				SR [95%,100%)	0.028***	(0.007)
As needed	0.041***	(0.009)		SR 100%	0.030***	(0.006)
<= 30 hrs/week	0.038***	(0.010)		**Skills**		
> 30 hrs/week	-0.021**	(0.009)		# test	0.0015*	(0.0009)
Response time				Av. score	0.037***	(0.005)
< 24 hrs	-0.054***	(0.005)		**Agency**		
< 3 days	-0.065***	(0.014)		Single worker	-0.034***	(0.014)
3+ days	-0.175***	(0.008)		Multi worker	-0.057***	(0.014)
Observations	100,023	$\mathbf{R^2}$	0.586			

Notes: The table reports the coefficients estimated from equation (2). Country and sector fixed effects are included but not reported. *: significant at the 10% level, **: significant at the 5% level, *** significant at the 1% level.

Table A5: Pass-through to transacted wages: Real Exchange Rate

	(1)	(2)	(3)	(4)
	$\Delta_s w_{ijt}$	$\Delta_s w_{ijt}$	$\Delta_s w_{ijt}$	$\Delta_s w_{ijt}$
$\pi_{c,t_s} + \Delta_s e_{ct}$	0.139^{**}	0.154^{**}	0.148^{**}	0.166^{**}
	(0.061)	(0.065)	(0.064)	(0.069)
$\Delta_s w_{jt}$		0.653^{***}	0.954^{***}	
		(0.058)	(0.076)	
Observations	109669	109669	109669	109669
R-squared	0.00015	0.0060	0.0047	0.0030
Specification	OLS	OLS	2SLS	OLS
F stat 1st stage			226.0	

Notes: This table reestimates Table 3 imposing the restriction that $\beta_1 = \beta_2$. Specifications in all columns include country-sector-specific linear trends but they are not reported. Standard errors are clustered at the time-spell and country level. *: significant at the 10% level, **: significant at the 5% level, *** significant at the 1% level. First stage regressions are in Table A6.

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

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	$\Delta_s w_{jt}$	$\Delta_s w_{jt}$	$\Delta_s w_{jt}$	$\Delta_s w_{-ijt}$	$\Delta_s w_{jt}$	$\Delta_s w_t^{plac}$	$\Delta_s w_{jt}$	$\Delta_s w_{jt}$	$\Delta_s w_{jt}$
$\Delta_s e_{ct}$	0.017		0.018	0.017	0.017	-0.003	0.000	0.029**	0.000
	(0.012)		(0.013)	(0.012)	(0.012)	(0.003)	(0.018)	(0.012)	(0.000)
π_{c,t_s}	-0.051		-0.054	-0.049	-0.050	0.005	-0.084**	-0.006	0.000
	(0.034)		(0.037)	(0.034)	(0.034)	(0.004)	(0.042)	(0.032)	(0.000)
$\pi_{c,t_s} + \Delta_s e_{ct}$		0.019							
		(0.012)							
$\Delta_s e_t$	0.052***	0.052***	0.053***	0.045***	0.053***	-0.002**	0.052***	0.053***	0.019
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.001)	(0.002)	(0.003)	(0.175)
$\pi_{t-s,t}$	0.637***	0.636***	0.669***	0.620***	0.645***	-0.047***	0.595***	0.652***	-0.525**
	(0.031)	(0.030)	(0.032)	(0.032)	(0.031)	(0.008)	(0.028)	(0.033)	(0.227)
$\Delta_s e_t^{plac}$					0.015***	0.012**			
					(0.003)	(0.005)			
$\pi_{t-s,t}^{plac}$					0.146***	0.224***			
					(0.029)	(0.040)			
Observations	109669	109669	80727	109669	109669	109669	109669	109669	226559

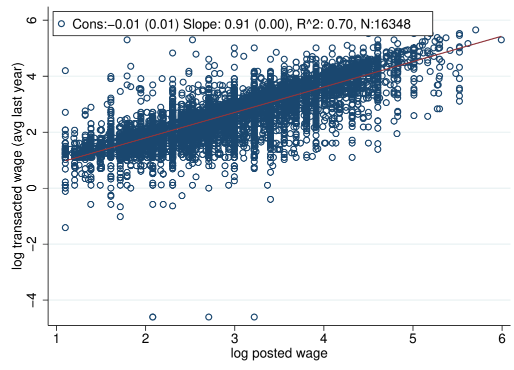
Notes: Columns 1 and 2 report the first stage corresponding to column 3 in Table (3) and in table (A5), respectively. Columns 3-6 report the first stage corresponding to columns 1-3 in Table (A7). Specifications in these columns include country-sector-specific linear trends but they are not reported. Standard errors are clustered at the time-spell and country level. Colums 7-8 report the first stage corresponding to columns 4-5 in Table (A7). Column 9 reports the first stage corresponding to column 7 in Table (A7). *: significant at the 10% level, **: significant at the 5% level, *** significant at the 1% level.

Table A7: Pass-through to transacted wages: Robustness

	(1) $\Delta_s w_{ijt}$	(2) $\Delta_s w_{ijt}$	(3) $\Delta_s w_{ijt}$	(4) $\Delta_s w_{ijt}$	(5) $\Delta_s w_{ijt}$	(6) $\Delta_s w_{ijt}$	(7) $\Delta_s w_{ijt}$
$\Delta_s e_{ct}$	0.166**	0.148**	0.149**	0.125	0.144**	0.084***	0.081***
	(0.074)	(0.063)	(0.063)	(0.094)	(0.059)	(0.028)	(0.015)
π_{c,t_s}	0.224*	0.184*	0.183*	0.171	0.124	0.095	0.092***
	(0.133)	(0.101)	(0.102)	(0.182)	(0.114)	(0.086)	(0.032)
$\Delta_s w_{jt}$	1.257***		0.899***	0.987***	0.961***		
	(0.099)		(0.062)	(0.090)	(0.095)		
$\Delta_s w_{-ijt}$		0.988***					1.055***
		(0.072)					(0.054)
$\Delta_s w_{jt}^{plac}$			-0.371**				
			(0.167)				
Observations	80727	109669	109669	109669	109669	226559	226559
Test $\beta_1 = \beta_2$	0.63	0.70	0.72	0.75	0.82	0.90	0.000066
Specification	2SLS	2SLS	2SLS	2SLS	2SLS	OLS	2SLS
F stat 1st stage	217.2	198.0	80.4	244.4	201.9		5.65

Notes: Column 1 reestimates column 3 in Table 3 using the sample of non-zero wage changes. Column 2 reestimates column 3 in Table 3 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 3 reestimates column 3 in Table 3 and includes the change in wages of workers that are predicted to be the least likely competitors of a given worker. These three columns include country-sector-specific linear trends. Column 4 reestimates the specification in columns 3 of Table 3 without controlling for country-sector-specific trends. Columns 5 reestimate the specification in column 3 of Table 3 without controlling for time-spell fixed effects. In columns 1-5, standard errors are clustered at the time-spell and country level. Columns 6-7 report the results from estimating equation (19). 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.

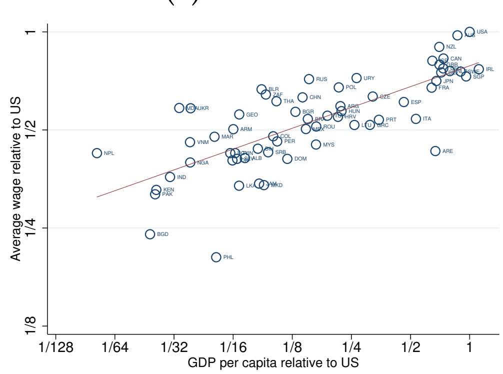
Figure A.1: Ask vs. transacted wages



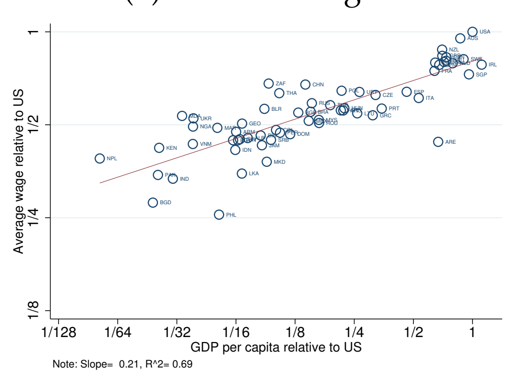
Notes: The figure shows the scatter plot between a worker's ask wage (x-axis) and the worker's average transacted wage (y-axis). Average transacted wages are computed using wages in the job-level data that were received within the year around the date of the ask wage.

Figure A.2: ask wages and GDP per capita relative to the US

(a) Raw data



(b) Residual wages

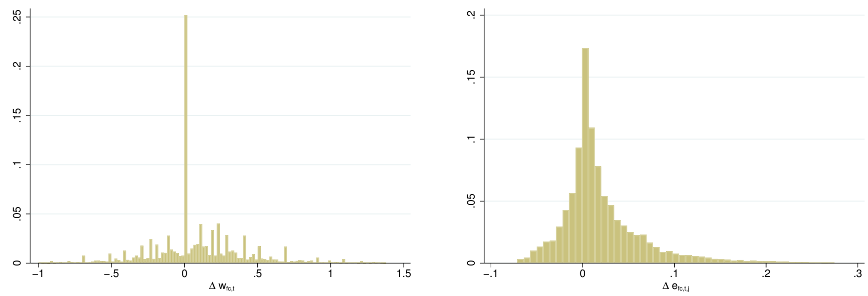


Notes: The x-axis reports the (log of) the relative GDP per capita in US dollars, taken from the World Development Indicators (WDI) collected by the World Bank. These panels on the left-hand side report the (log of) the average ask wage in country c relative to the US.

Table A8: Offshoring by occupation

Occupation Platform	Measure 1	SOC title	SOC code	Measure 1	Occupation Platform	Measure 1	SOC title	SOC code	Measure 1
ERP / CRM Implementation Spc.	0.95	Computer Systems Anlst.	15-1211	0.95	Graphics Design	0.82	Graphic Designers	27-1024	0.81
Mobile Dev.	0.90	Sw. Dev.	15-1252	0.89	Scripts & Utilities Dev.	0.81	Computer Pgmr.	15-1251	0.81
Interior Designers	0.90	Interior Designers	27-1025	0.90	Mechanical Engineers	0.81	Mechanical Engineers	17-2141	0.81
Medical Translators Prof.	0.90	Interpreters and Translators	27-3091	0.88	Video Production Spc.	0.81	Producers and Directors	27-2012	0.81
Animators	0.89	Special Effects Artists and Animators	27-1014	0.88	Logo & Brand Designers	0.81	Graphic Designers	27-1024	0.81
Technical Support Representatives	0.89	Computer User Support Spc.	15-1232	0.89	Email & Mktg. Autom. Mgr. & Cnslt.	0.80	Search Mktg. Strategists	13-1161	0.82
Machine Learning Spc. & Anlst.	0.89	Data Scientists	15-2051	0.85	Electrical Engineers	0.80	Electrical Engineers	17-2071	0.80
Architects	0.89	Architects, excl Landscape and Naval	17-1011	0.89	QA & Testing Spc.	0.80	Sw. QA Anlst. & Testers	15-1253	0.80
Data Mining Management	0.89	Data Scientists	15-2051	0.85	Contract Manufacturers	0.80	Architectural and Civil Drafters	17-3011	0.80
Information Security Spc. & Cnslt.	0.88	Information Security Anlst.	15-1212	0.88	Project Mgr.	0.79	Project Management Spc.	13-1082	0.79
Legal Translation Prof.	0.88	Interpreters and Translators	27-3091	0.88	Art Illustration	0.79	Fine Artists	27-1013	0.79
Virtual Assistants, Personal Assistants	0.88	Special Effects Artists and Animators	27-1014	0.88	Transcription Svss Prof.	0.78	Audio and Video Technicians	27-4011	0.77
General Translation	0.88	Foreign Lang. and Lit.Teachers, Pse	25-1124	0.88	Data Visualization Spc. & Anlst.	0.77	Data Scientists	15-2051	0.85
Data Entry Spc.	0.88	Data Entry Keyers	43-9021	0.88	Mktg. Strategy	0.76	Market Research Anlst. and Mktg. Spc.	13-1161	0.82
Game Dev.	0.88	Video Game Designers	15-1255	0.84	A/B Testing Spc.	0.76	Sw. and Web Dev., Pgmr., & Testers	15-1250	0.76
Desktop Sw. Dev.	0.87	Sw. Dev.	15-1252	0.89	Audio Production Spc.	0.76	Audio and Video Technicians	27-4011	0.77
Network & System Adm.	0.87	Network and Computer Systems Adm.	15-1244	0.87	Chemical Engineers	0.71	Chemical Engineers	17-2041	0.71
Data Extraction / ETL Spc.	0.87	Data Warehousing Spc.	15-1243	0.87	Quantitative Analysis Spc.	0.70	Data Scientists	15-2051	0.85
Other - Admin Support Prof.	0.87	Order Clerks	43-4151	0.87	Accounting	0.68	Accountants and Auditors	13-2011	0.68
Lead Generation Prof.	0.87	Mktg. Mgr.	11-2021	0.87	Technical Writers	0.64	Technical Writers	27-3042	0.64
Web Research Spc.	0.87	Data Scientists	15-2051	0.85	Display Advertising Spc.	0.64	Search Mktg. Strategists	13-1161	0.82
3D Modeling Cad	0.87	Special Effects Artists and Animators	27-1014	0.88	Copywriters	0.61	Writers and Authors	27-3043	0.55
Technical Translation Prof.	0.87	Interpreters and Translators	27-3091	0.88	Public Relations (PR) Prof.	0.57	Public Relations Spc.	27-3031	0.57
Social Media Mktg. (SMM) Spc.	0.86	Search Mktg. Strategists	13-1161	0.82	Article Blog Writing	0.57	Poets, Lyricists and Creative Writers	27-3043	0.55
TeleMktg. & Telesales Spc.	0.85	Telemarketers	41-9041	0.85	Family Law Prof. & Cnslt.	0.56	Lawyers	23-1011	0.40
Ecommerce Pgmr. & Dev.	0.85	Search Mktg. Strategists	13-1161	0.82	Proofreaders & Editors	0.56	Editors	27-3041	0.56
Product Management Prof. & Cnslt.	0.84	Logistics Anlst.	13-1081	0.84	Voice Talent Artists	0.55	Musicians and Singers	27-2042	0.55
Other Sales & Mktg. Spc.	0.84	Search Mktg. Strategists	13-1161	0.82	Management Cnslt.	0.53	Management Anlst.	13-1111	0.53
Database Administration	0.84	Database Adm.	15-1242	0.84	Other Writing Svss Prof.	0.51	Writers and Authors	27-3043	0.55
Web Designers, Mobile Designers	0.84	Web and Digital Interface Designers	15-1255	0.84	Creative Writers	0.48	Poets, Lyricists and Creative Writers	27-3043	0.55
Search Engine Mktg. (SEM) Spc.	0.83	Search Mktg. Strategists	13-1161	0.82	Intellectual Prop. Law Prof. & Cnslt.	0.38	Lawyers	23-1011	0.40
Customer Svs & Tech Support Reps	0.83	Customer Svs Representatives	43-4051	0.83	Paralegal Prof.	0.36	Paralegals and Legal Assistants	23-2011	0.36
Search Engine Optimization (SEO) Spc.	0.83	Mkt. Research Anlst. and Mktg. Spc.	13-1161	0.82	Resumes & Cover Letters Writers	0.35	Educational, Gdnc., and Career Adv.	21-1012	0.35
Market & Customer Researchers	0.83	Mkt. Research Anlst. and Mktg. Spc.	13-1161	0.82	Contract Law	0.33	Lawyers	23-1011	0.40
Photographers	0.83	Photographers	27-4021	0.83	Corporate Law Prof. & Cnslt.	0.33	Lawyers	23-1011	0.40
Presentation Designers & Dev.	0.82	Art Directors	27-1011	0.82	Grant Writers	0.30	Fundraisers	13-1131	0.30

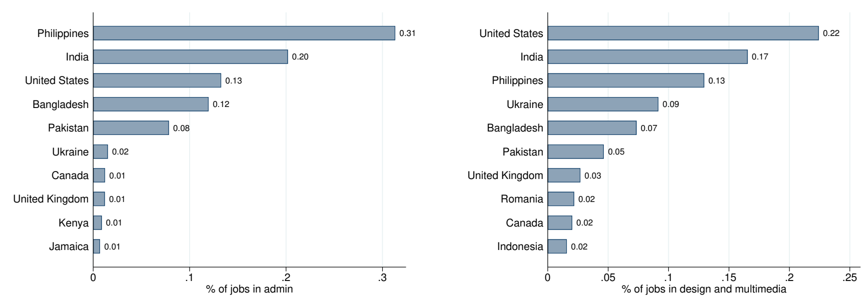
Figure A.3: Distribution of wage and exchange rate changes: transacted wages



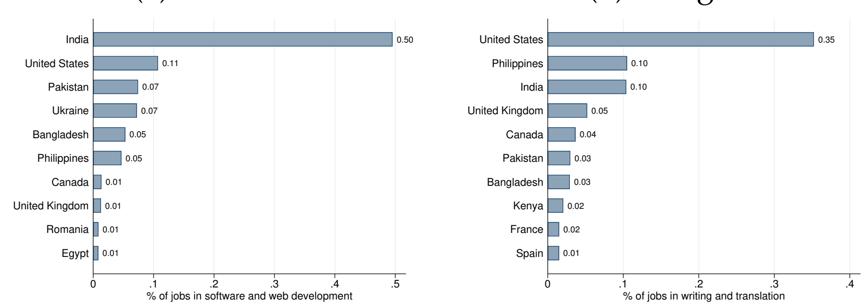
(a) Wage changes (b) Exchange rate changes

Notes: Panel (a) reports the distribution of hourly wage changes in between subsequent hourly jobs in the job-level data. Panel (b) reports the distribution of exchange rate changes for each time-spell in between subsequent jobs. The figure shows the variation in these variables behind the estimation of equation (15).

Figure A.4: Sectorial variation in instrumental variable



(a) Admin (b) Design



(c) Web (d) Writing

Notes: This figure reports the variation behind the sectoral shares used in the instrumental variable $\sum_c s_{cjt}\left[\pi_{ct_s} + \Delta_s e_{ct}\right]$.

A.2 Blinder-Oaxaca Decomposition

We now further evaluate whether the observed differences in wages across countries are driven by cross-country differences in workers' skills or by differences in returns to skills across countries. With this in mind, we conduct a 'Blinder-Oaxaca' decomposition (Blinder, 1973; Oaxaca, 1973) of the observed wage differentials. We start by writing the log-wage of remote worker i in country c as:

$$w_i^c = \beta_c^{'} X_i^c + \varepsilon_i^c. \tag{A.2.1}$$

Here, X_i^c is a vector containing worker characteristics (skills, experience, quality ratings, etc.) and a constant. β_c is a vector of country-specific slope parameters and an intercept. Thus, wages reflect not only differences in efficiency units of labor, but also how those units are rewarded in each country. Note that the relative wage between country c and the US can be written as:

$$rer_{c,us}^{w} \equiv \mathbb{E}\left(w_i^c\right) - \mathbb{E}\left(w_i^c\right) = \beta_i' \mathbb{E}\left(X_i^c\right) - \beta_{us}' \mathbb{E}\left(X_{i,us}\right),$$

where we used that $\mathbb{E}\left(\varepsilon_i^c\right) = 0$.

The goal of the 'Blinder-Oaxaca' decomposition is to evaluate whether observed wage differentials across countries are driven by differences in workers' characteristics X_i^c or by differences in the returns to those skills, β_c. With this in mind, we can re-arrange equation (A.2.1) as:

$$rer_{c,us}^{w} = \underbrace{\beta_{us}' \left[\mathbb{E}\left(X_i^c\right) - \mathbb{E}\left(X_i^{us}\right)\right]}_{\text{Endowment}} + \underbrace{\left[\beta_i' - \beta_{us}'\right] \mathbb{E}\left(X_i^c\right)}_{\text{Returns}}. \tag{A.2.2}$$

Equation (A.2.2) states that relative wages can be written as the sum of two terms. The first term, labeled 'Endowment', captures differences in wages predicted by the observed differences in workers' characteristics in country c vs the US, $\left[\mathbb{E}\left(X_i^c\right) - \mathbb{E}\left(X_i^{us}\right)\right]$. The second term, labeled 'Returns', captures differences in wages predicted by the estimated differences in returns across countries, $\left[\beta_i' - \beta_{us}'\right]$.

We implement this decomposition to the wage differential for the five largest countries in terms of the number of workers, all of which exhibit large differences in wages relative to the US. The vector of worker characteristics in the regression includes: i) the experience variables (past earnings and number of jobs), ii) the quality ratings (success ratings and whether the worker is "Top Rated"), iii) 91 detailed occupation-level fixed effects indicating whether the worker is listed in an occupation, and iv) 106 dummy variables for each test that indicate if the worker has taken the test, along with 106 variables indicating the worker's score in each test, (v) dummies for availability (dummies for Full/part-time, and dummies for response time), and (vi) dummies for whether the worker works in an agency.

Table A9 reports the results of this decomposition. The second column reports differences in average wages between country c and the US. The second column reports the wage differentials predicted by the term labeled 'Endowment'. While there are some differences in worker characteristics across countries, these differences are not strongly correlated with cross-country differences in GDP per capita. In fact, workers in India and Ukraine appear to have similar average endowments as their counterparts in the US. In contrast, the last column shows the wage differentials predicted by the term labeled 'Returns'. Differences in returns are the main drivers of wage-based real exchange rates with the US.

Table A9: Blinder-Oaxaca decomposition of wages

	$rer^{w}_{c,us}$	Endowment	Returns
Bangladesh	-1.45	-0.21	-1.24
India	-1.04	0.03	-1.07
Pakistan	-1.10	-0.13	-0.96
Philippines	-1.55	-0.33	-1.22
Ukraine	-0.49	0.09	-0.58

Notes: The table reports the results from Blinder-Oaxaca decomposition in equation (A.2.2).

A.3 Derivation of Equations (13) and (14)

The change in worker's i wage is:

$$dw_{ijt} = d\omega_{jct} + dz_{ijt}, \tag{A.3.1}$$

where the change in wages per efficiency units is given by

$$d\omega_{jct} = \frac{\theta}{\rho+\theta} db_{jct} + \frac{1}{\rho+\theta} d\varphi_{jct} + \frac{\rho-\eta}{\rho+\theta} p_{jt} + \frac{1}{\rho+\theta}\left[\eta p_t + y_t\right]. \tag{A.3.2}$$

Differentiating (7) yields

$$dp_{jt} = \frac{1}{1-\rho} da_{jt} + d\omega_{jt},$$

which can be rewritten as

$$dp_{jt} = \frac{\theta}{\theta+\eta} db_{jt} + \frac{1}{\theta+\eta}\left[d\varphi_{jt} + \frac{\rho+\theta}{1-\rho} da_{jt}\right] + \frac{1}{\theta+\eta}\left[\eta dp_t + dy_t\right], \tag{A.3.3}$$

Substituting (12) into (12) and (12) yields:

$$\begin{aligned}
d\omega_{jct} &= \frac{\theta}{\rho+\theta}\left[de_{ct} + \pi_{ct}\right] + \frac{1}{\rho+\theta}\left[d\varphi_{ct} + \theta\gamma_{jct}\right] + \frac{\rho-\eta}{\rho+\theta} p_{jt} + \frac{1}{\rho+\theta}\left[\eta p_t + y_t\right]. \\
dp_{jt} &= \frac{\theta}{\theta+\eta}\left[de_{ct} + \pi_{ct}\right] + \frac{1}{\theta+\eta}\left[d\varphi_{jt} + \frac{\rho+\theta}{1-\rho} da_{jt} + \theta\gamma_{jct} + \left[\eta dp_t + dy_t\right]\right],
\end{aligned}$$

Let $dz_{jt} \equiv \sum s_{jct}\mathbb{E}_c dz_{ijt}$. Then, we can write:

$$\begin{aligned}
dz_{jt} &\equiv \sum s_{jct}\mathbb{E}_c dz_{ijt} \\
dp_{jt} &= \frac{1}{1-\rho} da_{jt} + \sum_c s_{jct}\mathbb{E}_c\left[d\omega_{jct} + dz_{ijt}\right] - dz_{jt}, \\
&= \frac{1}{1-\rho} da_{jt} - dz_{jt} + \sum_c s_{jct}\mathbb{E}_c\left[dw_{ijt}\right],
\end{aligned}$$

Finally, we define the index of wage changes as:

$$dw_{jt} \equiv \sum_c s_{jct}\mathbb{E}_c\left[dw_{ijt}\right].$$

Note that we can write:

$$dp_{jt} = \frac{1}{1-\rho} da_{jt} + dw_{jt} - dz_{jt}, \tag{A.3.4}$$

and

$$dw_{jt} = \frac{\theta}{\theta+\eta}\left[de_{ct}+\pi_{ct}\right] + \frac{1}{\theta+\eta}\left[\theta\gamma_{jct} + d\varphi_{jt} + \frac{\rho-\eta}{1-\rho}da_{jt} + \left[\eta dp_t + dy_t\right]\right] + dz_{jt}, \tag{A.3.5}$$

Substituing (A.3.2), (A.3.4), and (A.3.5) into (A.3.4), we obtain

$$dw_{ijt} = \frac{\theta}{\rho+\theta}\left[de_{ct}+\pi_{ct}\right] + \frac{\rho-\eta}{\rho+\theta}dw_{jt} + d\psi_{jct} + d\psi_{jt} + d\psi_t + dz_{ijt}.$$

$$\begin{aligned}
d\psi_{jct} &\equiv \frac{1}{\rho+\theta}\left[d\varphi_{jct}+\theta\gamma_{jct}\right] \\
d\psi_{jt} &= \frac{\rho-\eta}{\rho+\theta}\left[\frac{1}{1-\rho}da_{jt} - dz_{jt}\right] \\
d\psi_t &= \frac{1}{\rho+\theta}\left[\eta p_t + y_t\right]
\end{aligned}$$

and

$$\begin{aligned}
dw_{jt} &= \frac{\theta}{\theta+\eta}\left[de_{ct}+\pi_{ct}\right] + d\phi_{jt} + d\phi_t, \\
d\phi_{jt} &= \frac{1}{\theta+\eta}\left[\theta\gamma_{jct} + d\varphi_{jt} + \frac{\rho-\eta}{1-\rho}da_{jt}\right] + dz_{jt} \\
d\phi_t &= \left[\eta dp_t + dy_t\right]
\end{aligned}$$