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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 location of the worker accounts for over a third of the variance in wages. The observed wage differences are strongly correlated to the GDP per capita of the worker's country. 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 provide a new measure on which jobs are easier to offshore that is based on the prevalence of cross-border contracts rather than on subjective job characteristics, and show that there is substantial heterogeneity in the offshorability of remote occupations.

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1 Introduction

An increasing number of jobs are being done remotely, a trend that accelerated dramatically during the COVID pandemic.[1] Remote work can be done from anywhere, which makes it 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 remote wages converge across countries? Will remote wages be more sensitive 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 or mobile phone, and encompass a wide range of occupations, ranging from accountants to web developers. This makes the platform the ideal marketplace for studying the international price of remote work. Second, the dataset is very rich: in addition to hourly wages, it contains extensive information on worker characteristics such as experience, earnings, quality ratings, and standardized test scores and certifications. This information is essential for understanding cross-country wage differences, as it facilitates the comparison of workers around the world. Third, the data record the workers' job histories in the platform (wages, earnings, and start date of each job),

[1] OECD (2021).

[2] See Blinder and Krueger (2013). We use the term remote work to refer to work that does not need to be carried out in-person at specific locations.

[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).

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 over a third of the variance of wages in the data –more than twice 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 that workers could receive in their local labor markets. We note, however, that remote wages are substantially more equalized than income per capita across countries and US states: 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 18%. This implies that (partial) ERPT into local currency wages is 82%, 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 (22% 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 instrument changes in competitors' wages with the inflation and the exchange rate changes in the competitors' countries. We find that, in response to a 1% increase in competitors' wages driven by foreign shocks, the wage of a worker increases by 0.5%. This means, 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 $0.5 \times [10\% \times 20\%] = 1\%$ 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 in the future. 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 measure offshorability based on the frequency with which US employers assign contracts to foreign workers in an occupation. In particular, we compute an offshorability index that is 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 can be 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 of offshorability across remote occupations: Interior Design jobs are three times more likely to be offshored than Grant Writers jobs. We also document substantial heterogeneity in offshorability 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. Overall, the variability in offshorability within SOC categories accounts for 35% of the variation in offshorability across the more disaggregated categories in the platform. Finally, we show that wages are less dispersed in more easily offshored occupations, providing evidence that offshorability 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 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 degree of offshorability 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 will 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

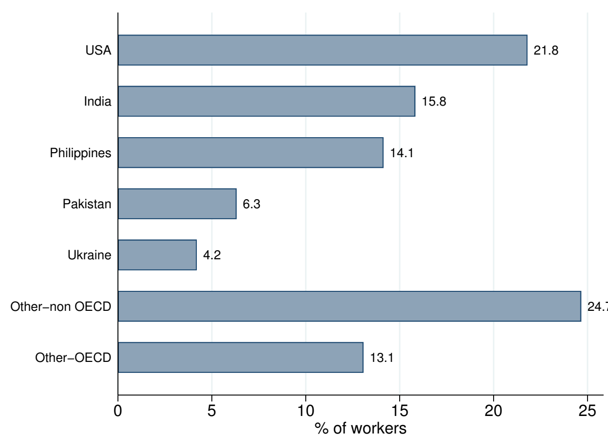
We build our second dataset by scraping the job histories of a subset of 30,520 workers that were present in the January 2019 worker-level dataset. The unit of observation in this dataset is a job or contract, and we will refer to these data as the 'job-level' data. The dataset can be merged with the 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 live in non-OECD countries.

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

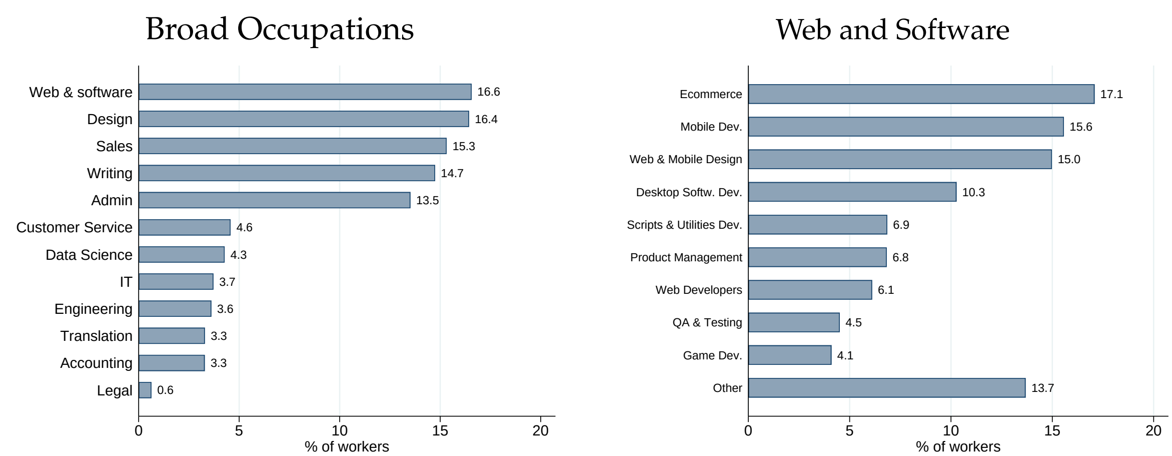


Notes: The figure shows the distribution of workers across countries in the worker-level data.

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 wage 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 can observe the identity and location of the employer. Figure 3 compares the geographical distribution of the 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

Table 1: Summary statistics: worker-level data

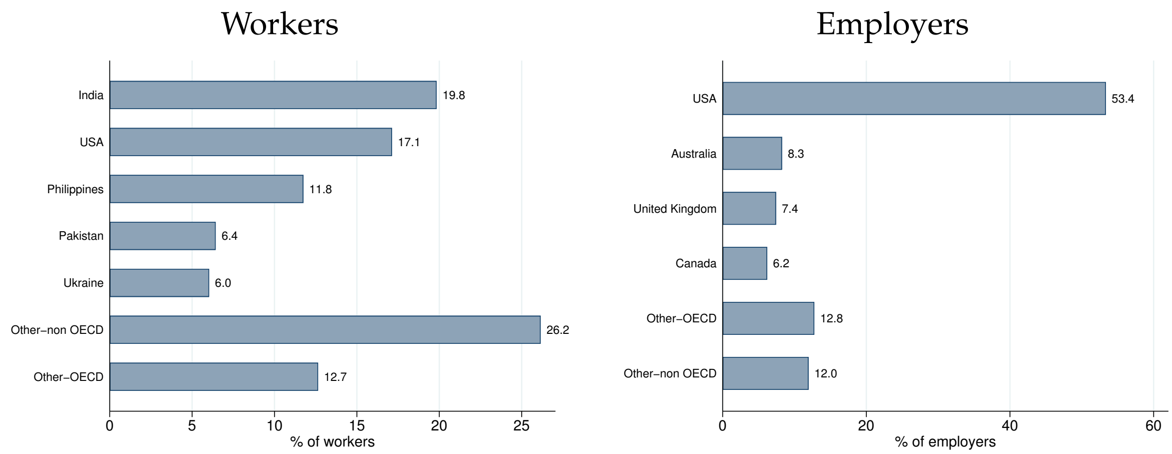
	Mean	Median	St. Dev.	5 pct	95 pct
Hourly wage	25	18	27	5	75
Number of jobs	69	10	642	1	147
Hours worked	1,801	408	3,388	4	8,515
Total earnings	18,667	4,000	62,558	20	90,000
Number of tests	4	3	4	1	10
Average score	4.23	4.25	0.50	3.38	5

	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.

located in just 4 countries: the US (53.4%), Australia (8.3%), the UK (7.4%), and Canada (6.2%). While the US is a large source of both workers and employers, most employers (88%) are located in OECD countries, while most workers (70%) are located in non-OECD countries. This indicates that many workers from Non-OECD countries work for employers in OECD countries. In fact, for 87% of the jobs in our sample, the worker and the employer are located in different countries. 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.

2.3 Wage determinants

We conclude our data description by evaluating how hourly wages correlate with workers' characteristics. With that in mind, we estimate the following OLS regression using the worker-level data:

$$w_i = \mathbb{C}_i + \mathbb{S}_i + \boldsymbol{\beta}' \mathbf{X_i} + \varepsilon_i. \tag{1}$$

Here, w_i is the log-hourly wage of worker i, $\mathbb{C}_i$ is the full set of country fixed effects, $\mathbb{S}_i$ is the full set of occupation fixed effects (recall that workers can be listed in multiple occupations), and 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 (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).

The results from this regression are reported in Table 2. The coefficient on past earnings is positive and statistically different from zero. The coefficients on the number of jobs dummies are monotonically increasing, indicating that more experienced workers earn higher wages relative to less-experienced workers. Hourly wages also increase with the number of tests that the worker has taken, and with the worker's average score in these tests. Quality variables are also positively correlated with hourly wages—Top Rated workers earn an hourly wage premium of 0.312 log points. In addition, the coefficients of the success rate dummies are monotonically increasing. The omitted category is a missing success rating, indicating that workers with a low rating (i.e., success ratings of less than 70%) face a wage penalty, but workers with a 100% rating do not earn more than those with no rating.

The table also shows that workers that work through agencies earn on average 0.04 to 0.06 log points less than workers that work independently. This could result from agencies helping new workers find a job in order to obtain a good reputation in the platform and become self-employed. Finally, workers who tend to respond faster and work more hours in a week tend to earn less than other workers. This could be explained by part-time workers being more selective when deciding which jobs to accept.

Wage dispersion within and across countries: We now evaluate how wages vary within and across countries. A regression of log-wages on the set of country fixed effects has an R^2 of 0.41. This indicates that more than 40% of the overall ask wage dispersion can be accounted for by the variance of average wages across-countries. This is economically large since the overall wage dispersion accounted for by the full set of controls in equation (1) is 0.586. In Table A3 in the Appendix, we formalize this by conducting a variance decomposition of equation (1). We show that the variance in the worker's country of origin accounts for 26% of the dispersion in wages, and that the covariance between the country of origin and the other observables account for an additional 12% (the variance of the other observables account for 16% of the dispersion in wages, and the residual vari-

Table 2: 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 (1). 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.

ance is 45%). In that table, we also show similar results when replacing ask wages with transacted wages—in that case, the variance in a worker's country of origin accounts for 34% of the dispersion of wages, and the covariance between the country of origin and other observables accounts for 5%. Given this result, in the next section we provide a comprehensive picture of the cross-country differences in average wages.

3 Remote wages and workers' locations

This section documents differences in wages across remote workers that are located in different geographical areas. We start by documenting wage differences across countries. To do so, we first compute average wages in each country relative to the US after residualizing wages for worker observable characteristics. We estimate these relative wages both in the worker-level and the job-level datasets.

Using the worker-level data, the country fixed effects estimated in equation (1) can be used to obtain these residualized average wages. An advantage of the job-level dataset is that it contains information on both workers and employers, although for a subsample of workers. Using these data, we estimate

$$w_{fi} = \mathbb{C}_i + \mathbb{D}_f + \mathbb{I}_{i=f} + \mathbb{S}_i + \boldsymbol{\beta}'\boldsymbol{X_i} + \varepsilon_{fi}. \quad (2)$$

Here, w_{fi} is the (log) wage paid by employer f to worker i in a given job. Equation (2) extends the specification in (1) with a set of country-of-employer fixed effects $\mathbb{D}_f$ and an indicator $\mathbb{I}_{i=f}$ that is equal to one if the employer and worker are in the same country. The latter estimates the premium that employers pay for workers from their country.[6] The remaining controls are the same as those included in equation (1). Both in equations (1) and (2), the omitted country category is the US, so the country fixed effects measure average wages in each country relative to the average wage in the US.

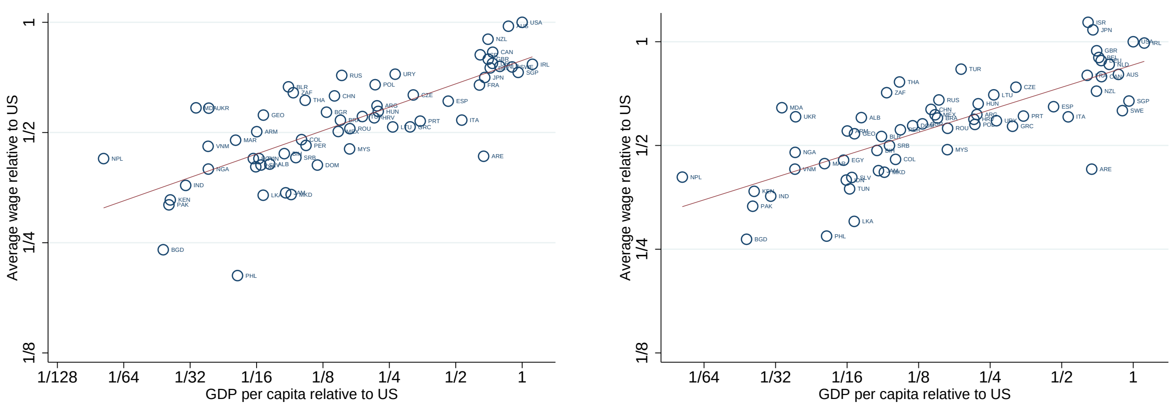
Figure 4 compares the relative wages to the relative GDP per capita of each of the 67 countries with at least 100 workers in our sample.[7] Panel (a) plots the average residualized relative wage estimated from equation (1) estimated from the worker-level data. Panel (b) plots the average residualized relative wage estimated from equation (2) using the job-level data. 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 relation is 0.21 (SE 0.025) in Panel (a) and 0.22 (SE 0.025) in Panel (b), and the R^2 are is 0.58 and 0.59, respectively. It is worth noting that the estimation in Panel (b) also controls for country-of-employer 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.

[6]The estimated coefficient on this dummy is 0.07 log-points, indicating that employers pay a premium for workers from their own country.

[7]Appendix Figures A.2 and A.3 show similar results when expanding the sample of countries to those with more than 50 workers, and when restricting the sample to countries with at least 500 workers.

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

(a) Worker-level data (ask wages) (b) Job-level data (transacted wages)



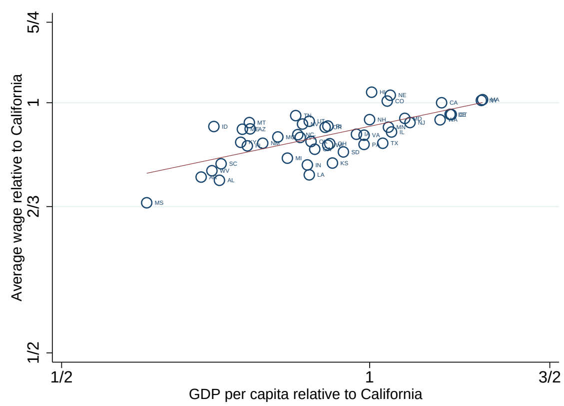
Notes: The x-axes report the (log of) the relative GDP per capita in US dollars, taken from the World Development Indicators (WDI). Panel (a) plots the average ask wage in each country relative to the US, obtained from the country fixed effects estimated in equation (1) with the worker-level data. Panel (b) reports the average transacted wage in each country relative to the US obtained from the country fixed effects estimated in equation (2) with the job-level data. The red lines show the linear fit of the data. The estimated slope is 0.21 (0.025) in panel (a) and 0.22 (0.025) in panel (b), and the R^2 are 0.58 and 0.59, respectively.

Decomposing wage differentials The previous results show that wage differences across countries cannot be explained by differences in average worker characteristics, occupational 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 (1), 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.

3.1 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. In particular, we reestimate equations (1) and (2) for the subsample of remote workers that are located in the US, and substitute the country fixed effects $\mathbb{C}_i$ for a full set of state fixed effects. 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 in California. 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] This figure plots the average residualized relative wage estimated from equation (1) using the worker-level (unfortunately, the worker's state is not available in the job-level data, respectively). 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 (1) 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.

[8]Notably, we exclude North Dakota, Wyoming, and Alaska that only have 18, 25, and 26 workers respectively and for which the state dummy is imprecisely estimated. Appendix Figure A.5 show similar results when including all states.

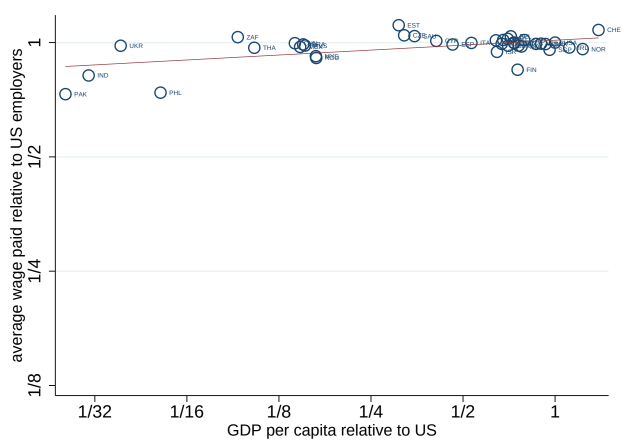
3.2 Pricing to market

This section evaluates 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.[9]

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.

The figure shows that workers 'price to market' —i.e., they get paid more when working for employers from richer countries. The slope of this relation is 0.06, with a standard

[9] Appendix Figure A.4 shows that the results in Figure 6 do not hinge on the sample of countries.

error of 0.016. 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 relation 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). We underscore this point in panel b of Figure 4, which already controls for country-of-employer fixed effects.

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. The market is competitive: a representative firm hires workers to produce a final good, taking wages as given. The production function for the final good is:

$$Y_t = \left[\sum_c A_{ct}^{\frac{1}{\rho}} L_{ct}^{\frac{\rho-1}{\rho}} \right]^{\frac{\rho}{\rho-1}}, \tag{4}$$

where L_{ct} denotes efficiency units of labor from location c, A_{ct} is a factor augmenting technology term which acts as a demand shifter, and ρ is the elasticity of substitution across workers from different locations. Equation (4) assumes that efficiency units of labor from the same locations are perfect substitutes. On the other hand, units from different locations can be imperfect substitutes if $\rho < \infty$.

Let Ω_{ct} denote the dollar wage per efficiency unit of labor from location c. Cost minimization implies that

$$L_{ct} = A_{ct} \left[\frac{\Omega_{ct}}{P_t} \right]^{-\rho} Y_t, \tag{5}$$

and that the unit cost for producing the final good is

$$P_t = \left[\sum_c A_{ct}\Omega_{ct}^{1-\rho}\right]^{\frac{1}{1-\rho}}, \tag{6}$$

with costs shares given by $s_{ct} \equiv \frac{\Omega_{ct}L_{ct}}{P_t Y_t} = \frac{A_{ct}\Omega_{ct}^{1-\rho}}{\sum_c A_{ct}\Omega_{ct}^{1-\rho}}$.

Remote labor supply: Each location is inhabited by a continuum of workers indexed by i. Each worker is endowed with Z_{it} efficiency units of labor and can work in the remote or in the local labor market. In the local labor market, workers earn a wage given by $Z_{it} \times B_{ct}/H_i$, where B_{ct} is the wage per efficiency unit of labor in the local labor market, and H_i 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.[10] A worker chooses to work remotely if and only if the wage for remote labor exceeds the wage paid in the local labor market. Thus, there exists a cutoff cost for working in the local labor market given by:

$$H_i \geq \underline{H}_{ct} \equiv B_{ct}/\Omega_{ct}, \tag{7}$$

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

$$L_{ct} = N_{ct} \times Z_{ct} \times [1 - G(\underline{H}_{ct})] = \tilde{N}_{ct}\left[\frac{\Omega_{ct}}{B_{ct}}\right]^\theta, \tag{8}$$

where $Z_{ct} \equiv \mathbb{E}_c[Z_{it}]$ denotes the average efficiency units of labor for workers from location c, and $\tilde{N}_{ct} \equiv N_{ct}Z_{ct}\kappa_c^\theta$ collects supply shifters other than B_{ct}. Equation (8) states that the labor supply elasticity is given θ.

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

Equilibrium: Combining equations (5) and (8), and using lowercase to denote variables in logs, we obtain the equilibrium wage per efficiency unit of remote labor in location c:

$$\omega_{ct} = \frac{\theta}{\rho+\theta} b_{ct} + \frac{1}{\rho+\theta} \varphi_{ct} + \frac{\rho}{\rho+\theta} p_t + \frac{1}{\rho+\theta} y_t, \tag{9}$$

where $\varphi_{ct} \equiv a_{ct} - \tilde{n}_{ct}$ collects the location-specific supply and demand shifters.

Remote wages and workers' locations: We now evaluate differences in wages across remote workers. Let $w_{it} \equiv \omega_{ct} + z_{it}$ denote the log-wage per unit of time of remote worker i in location c (i.e., the equivalent to hourly wages in the platform). Then:

$$w_{it} = \frac{\theta}{\rho+\theta} b_{ct} + \frac{1}{\rho+\theta} \varphi_{ct} + \frac{\rho}{\rho+\theta} p_t + \frac{1}{\rho+\theta} y_t + z_{it}. \tag{10}$$

Equation (10) states that wage differences across workers can arise from differences in local wages, b_{ct}, location-specific demand and supply shifters, φ_{ct}, and from differences in the worker's efficiency, z_{it}. 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_{it}. If instead labor supply is close to being perfectly elastic, $\theta \to \infty$, wage differences are given by differences in local wages b_{ct} and differences in z_{it}. For finite values of ρ and θ, the elasticity of remote wages with respect to local wages is positive but less than one, $\frac{\theta}{\rho+\theta} < 1$.

We can now use equation (10) to interpret the results from Section 3. To do so, we note that the total wage bill in the local labor market c is given by $B_{ct} \times Z_{ct} \times N_{ct} \times G(\underline{H}_{ct})$. We can then write local wages per unit of time in location c as:

$$b_{ct} + z_{ct} = \alpha + gdp_{ct}, \tag{11}$$

where α is the log of the labor share and gdp_{ct} is the log of dollar GDP per local worker in location c. In practice, the latter is not observable, and we will approximate it with the GDP per capita in the location.[11] Under these assumptions, the location fixed effects estimated from equation (1) can be interpreted as:

$$\mathbb{C}_{i\in c} \propto \frac{\theta}{\rho+\theta} gdp_{ct} + \frac{1}{\rho+\theta} \varphi_{ct} + \mathbb{E}_c \left[z_{it} \perp X_i \right] - \frac{\theta}{\rho+\theta} z_{ct}, \tag{12}$$

[11] This is a good approximation if in the data the fraction of workers that work in the local market is close to 1, $G(\underline{H}_{ct}) \to 1$.

where $\mathbb{E}_c[z_{it} \perp X_i]$ denotes the average worker efficiency z_{it} in location c that is orthogonal to the vector of observable worker characteristics X_i used in the estimation of (1). Equation (12) states that the partial elasticity of average log wages with respect to gdp per capita is $\frac{\theta}{\rho+\theta}$. If the unobservable supply and demand shifters and productivities in (12) are uncorrelated to gdp_{ct}, 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_{ct} and z_{ct}, or if our controls X_i do not properly account for differences in worker efficiency 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:

$$db_{ct} \simeq \gamma_{ct} + \pi_{ct} + de_{ct}, \tag{13}$$

where γ_{ct} is the growth of local wages in constant local currency units, π_{ct} is the inflation rate, and de_{ct} is the change in the exchange rate denominated in dollars per unit of local currency.

Let $dx_t \equiv \sum s_{ct} dx_{ct}$ denote the cross-country average change in a variable, and let $\chi \equiv -dy_t/dp_t$ denote the elasticity of y_t with respect to the production cost p_t.[12] Differentiating equations (6), (10) and substituting yields:[13]

$$dw_{it} = \frac{\theta}{\rho+\theta}[de_{ct} + \pi_{ct}] + \frac{\rho-\chi}{\rho+\theta} dw_t + d\xi_{ct} + d\psi_t + dz_{it}, \tag{14}$$

with

$$dw_t \equiv \sum_c s_{ct} \mathbb{E}_c[dw_{it}] = \frac{\theta}{\theta+\chi}[de_t + \pi_t] + d\phi_t. \tag{15}$$

Here, dw_t is an index of wage changes in the remote market, $d\xi_{ct} \equiv \frac{1}{\rho+\theta}[d\varphi_{ct} + \theta\gamma_{ct}]$ collects location-specific supply and demand shifters, and $d\psi_t \equiv \frac{\rho-\chi}{\rho+\theta}\left[\frac{1}{1-\rho} da_t - dz_t\right]$ and $d\phi_t \equiv \frac{1}{\theta+\chi}\left[\theta\gamma_t + d\varphi_t + \frac{\rho-\chi}{1-\rho} da_t\right] + dz_t$ collects aggregate supply and demand shifters.

[12]If there is full pass-through from costs to final good prices, then χ is the elasticity of demand for the final good.

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

Equations (14) and (15) state that the partial exchange rate pass-through elasticity is $\frac{\theta}{\rho+\theta}$ and that the total exchange rate pass-through elasticity is $\frac{\theta}{\rho+\theta}\left[1+\frac{\rho-\chi}{\theta+\chi}s_{ct}\right]$. In addition, the equation states that wages respond to average wages in the remote market with an elasticity of $\frac{\rho-\chi}{\rho+\theta}$, and to changes in other countries exchange rates and inflation rates with an elasticity of $\frac{\theta}{\rho+\theta}\frac{\rho-\chi}{\theta+\chi}\times s_{c't}$.

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 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. 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).[14] 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-month. Finally, not all workers are observed each month, both because workers may not start new jobs in a particular month, and because our data only contains a subset of the jobs in the platform. With this in mind, we denote by $\Delta_s w_{it} \equiv w_{it} - w_{it-s}$ the log-change in the wage of a worker 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 A4 and Figure A.6 in the Appendix A.1. Finally, in 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 (14). Note that $\Delta_s w_t$ only varies across time spells, so that we can estimate equation (14)

[14] In contrast, 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.

as:

$$\Delta_s w_{it}^c = \beta_1 \Delta_s e_{ct} + \beta_2 \pi_{t-s,t}^c + \mathbb{C} \times s + \mathbb{T}_{t_s} + \epsilon_{it_s}. \tag{16}$$

Here $\beta_1 = \beta_2 = \frac{\theta}{\rho+\theta}$ and $\pi_{t-s,t}^c$ denotes the inflation rate in country c between periods $t-s$ and t. $\mathbb{C} \times s$ is the product between country fixed effects and the duration s of the time-spell, which control for the country-specific linear trends in the demand and supply shifters ξ_{ct}. Finally, $\mathbb{T}_{t_s}$ is a set of fixed effects for each time spell t_s that control for changes in w_t and for aggregate supply and demand shifters ψ_t. The error term is given by $\epsilon_{it_s} \equiv \Delta_s \tilde{z}_{it} + \Delta_s \tilde{\tilde{\xi}}_{ct}$, where the notation $\tilde{x}$ denotes the deviation of a variable from the time-spell average and its country trend. Equation (16) 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 (16) by OLS yields consistent estimates of β_1 if the error term ϵ_{it_s} is orthogonal to changes in exchange rates and inflation across countries, i.e. $cov(\Delta_s \tilde{z}_{it} + \Delta_s \tilde{\tilde{\xi}}_{ct}, \Delta_s e_{ct}) = 0$. This exclusion restriction requires changes in exchange rates to be uncorrelated to trend deviations in 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.[15] Finally, we note that we will test the restriction $\beta_1 = \beta_2$ empirically rather than imposing it in our estimation.

4.2.3 Estimating the effect of competitors' wages

According to equation (14), wages respond to changes in competitor's wages with an elasticity $\frac{\rho-\chi}{\rho+\theta}$. We cannot test this implication using equation (16), since $\Delta_s w_t$ is absorbed by the fixed-effects $\mathbb{T}_{t_s}$. To test this implication directly, we instead estimate the following equation:

$$\Delta_s w_{i,t}^c = \beta_1 \Delta_s e_{ct} + \beta_2 \pi_{c,t-s,t} + \beta_3 \Delta_s w_t + \mathbb{C} \times s + \varepsilon_{it_s}. \tag{17}$$

Where $\epsilon_{it_s} \equiv \Delta_s \hat{z}_{it} + \Delta_s \hat{\xi}_{ct} + \Delta_s \hat{\psi}_t$, and $\hat{x}$ denotes the deviation of a variable from the country trend. The OLS estimates of (17) are inconsistent if $\Delta_s w_t$ is correlated with ε_{it_s}, which would be the case if the detrended aggregate shifters $\Delta_s \hat{\phi}_t$ and $\Delta_s \hat{\psi}_t$ are correlated. We, therefore, pursue an IV approach. From equation (15), a natural instrument for $\Delta_s w_t$

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

is

$$\Delta_s \Theta_t \equiv \sum_c s_{ct} \left[\pi_{c,t-s,t} + \Delta_s e_{ct} \right], \tag{18}$$

which correlates with $\Delta_s w_t$ but is orthogonal to ε_{it_s} under the exclusion restriction.

Measuring changes in competitors' wages: To implement equation (17), we need to construct an index of average wage changes, $\Delta_s w_t \equiv \sum_c s_{ct} \mathbb{E}_c \left[\Delta_s w_{it} \right]$. Obtaining such an index is not straightforward, since as mentioned above, the set of workers observed in our data changes from period to period. Thus, for any given time spell t_s, data on $\Delta_s w_{it}$ is not observed for many workers.

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

$$w_{it} = \delta_i + \delta_t + v_{it},$$

where δ_i and δ_t are two sets of worker and time fixed effects, respectively. We construct a series of the wage index as the series of the estimated time fixed effects, i.e., $\Delta_s w_t = \Delta_s \delta_t$.[16] Finally, in building the instrument in (18), we proxy s_{ct} by the share of jobs performed by workers from country c throughout our sample.

4.2.4 Results

We present our estimates in Table 3. Column 1 shows the results from estimating equation (16) by OLS, which in addition to $\Delta_s e_{ct}$ and $\pi_{c,t-s,t}$ includes country-specific trends and time-spell fixed effects. We cluster standard errors at the country level. The estimated partial pass-through is elasticity is $\hat{\beta}_1 = 0.179$ 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

[16] This procedure recovers up to a first order approximation the time series of dw_t. To see this, note that from equation we have:

$$\begin{aligned} d\delta_t &= \frac{\theta}{\rho+\theta} \left[de_t + \pi_t \right] + \frac{1}{\rho+\theta} \left[d\varphi_t + \theta \gamma_t \right] + \frac{\theta+\chi}{\rho+\theta} dz_t + \frac{\rho-\chi}{\rho+\theta} \frac{1}{1-\rho} da_t + \frac{\rho-\chi}{\rho+\theta} dw_t \\ &= \frac{\theta+\chi}{\rho+\theta} dw_t + \frac{\rho-\chi}{\rho+\theta} dw_t = dw_t. \end{aligned}$$

currency move in tandem with the dollar exchange rate (with an elasticity of 0.82). The coefficient on inflation is similar, $\hat{\beta}_2 = 0.11$, though we cannot reject the null hypothesis that it is equal to zero. In addition, we cannot reject the null that $\hat{\beta}_1 = \hat{\beta}_2$. Column 2 shows that imposing the restriction $\beta_1 = \beta_2 = \frac{\theta}{\rho+\theta}$ yields a coefficient of 0.182.

Column 3 shows the results from estimating equation (17), which also controls for country-specific linear trends but includes $\Delta_s w_t$ instead of the time-spell fixed effects $\mathbb{T}_{t_s}$. Standard errors are clustered at the time-spell level. The coefficients on the dollar exchange rate and inflation are very close to those in Column 1 and given by $\hat{\beta}_1 = 0.179$ and $\hat{\beta}_2 = 0.051$. The coefficient on the aggregate wage index is $\hat{\beta}_3 = 0.823$ and statistically different from zero. A t-test fails to reject the null that $\beta_1 + \beta_3 = 1$. Column 4 shows similar results if we impose the restriction $\hat{\beta}_1 = \hat{\beta}_2$.

Finally, column 5 reports the 2SLS estimates in which we use $\sum_{c'} s_{c't}\pi_{c't-s,t}$ and $\sum_{c'} s_{c't}\Delta_s e_{c't}$ separately as instruments for $\Delta_s w_t$. The estimated coefficient on the exchange rates and inflation are almost identical to those in Column 3. More importantly, the coefficient on $\Delta_s w_t$ is 0.56, 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. Table A6 in the Appendix reports the first-stage regression and shows that the coefficients on $\sum_{c'} s_{c't}\pi_{c't-s,t}$ and $\sum_{c'} s_{c't}\Delta_s e_{c't}$ are statistically significant and 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 $0.56 \times [s_{c'} \times 1\%]$. Column 6 shows similar results if we impose the restriction $\hat{\beta}_1 = \hat{\beta}_2$.

Table 3: Wage changes and international shocks: job-level data

	(1)	(2)	(3)	(4)	(5)	(6)
	$\Delta_s w_{i,t}$	$\Delta_s w_{i,t}$	$\Delta_s w_{i,t}$	$\Delta_s w_{i,t}$	$\Delta_s w_{i,t}$	$\Delta_s w_{i,t}$
$\Delta_s e_{ct}$	0.179***		0.179***		0.185***	
	(0.065)		(0.029)		(0.029)	
$\pi_{c,t-s,t}$	0.110		0.051		0.086	
	(0.138)		(0.074)		(0.079)	
$\pi_{c,t-s,t} + \Delta_s e_{ct}$		0.182***		0.182***		0.189***
		(0.065)		(0.029)		(0.029)
$\Delta_s w_t$			0.823***	0.813***	0.560***	0.483***
			(0.061)	(0.061)	(0.201)	(0.187)
Observations	108068	108068	108529	108529	108529	108529
R-squared	0.082	0.082	0.041	0.041	0.041	0.041
Test $\beta_1 = \beta_2$	0.57		0.064		0.18	
Specification	OLS	OLS	OLS	OLS	2SLS	2SLS
F stat 1st stage					103.1	103.3

Notes: The table reports the results from estimating equations (16) and (17). All columns include country-specific linear trends. Columns 1-2 also include time-spell specific fixed effects and cluster standard errors at the country level. Columns 3-6 cluster standard errors at the time-spell 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 Table A4 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. Table A7 in the Appendix reports the results. Relative to the baseline results, the coefficient on the change in the domestic exchange rate in Column 5 decreases from the baseline value of 0.185 to 0.222, and the coefficient in domestic inflation increases from 0.086 to 0.132, although statistically insignificant (making the model-imposed constraint $\beta_1 = \beta_2$ harder to reject). In addition, the coefficient on competitors' wages increases from 0.56 to 0.718 (the sum of β_1 and β_3 increases to 0.94, and the null hypothesis of being equal to one cannot be rejected). 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 (14). In the model of Section 4.1, there is a continuum of workers, so that dependance vanishes. To further reduce concerns about the endogeneity of our regressor, we reestimate equation (14) using the leave-one-out index for the competitors' wages, $\Delta_s w_{-i,t} \equiv \sum_{l \neq i} \frac{s_{lt}}{1-s_{it}} \Delta_s w_{lt} = [\Delta_s w_t - s_{it} \Delta_s w_{it}] / [1 - s_{it}]$, where s_{it} is the market share of worker i.[17] Note also that if all workers have small market shares $s_{it} \to 0$ (as they do in practice), then $\Delta_s w_{-i,t} \to \Delta_s w_t$. The results of this alternative estimation are presented in Appendix Table A8, and coincide with our baseline estimation.

Alternative assumptions on country-trends: Table A10 in the Appendix reestimates equations (16) and (17) using alternative controls for the country-specific trends. Columns 1 to 3 do not control for country-specific trends. Columns 4 to 6 include the interaction between country fixed effects and spell-length fixed effects to flexibly control for (possibly non-linear) country-specific trends. 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 Ap-

[17]Note that equation (14) can also be written as

$$dw_{it} = \frac{\theta}{\tilde{\rho}_{it} + \theta + s_{it}\chi} [de_{ct} + \pi_{ct}] + \frac{\tilde{\rho}_{it} - \chi [1 - s_{it}]}{\tilde{\rho}_{it} + \theta + s_{it}\chi} dw_{-it} + \frac{d\xi_{ct} + d\psi_t + dz_{it}}{\tilde{\rho}_{it} + \theta + s_{it}\chi}, \tag{19}$$

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

pendix.[18] In this case, we can estimate the partial pass-through elasticities from equation

$$\Delta w_i = b_1 \Delta e_c + b_2 \pi_c + \mathbb{S}^j + \mu_i, \tag{20}$$

where Δx represents the change in a variable between the two periods, and $\mathbb{S}^j$ is a vector of occupation fixed effects. We omitted time subscripts to highlight that we only have one observation per worker. Equation (20) is the worker-level data analog to (16). 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 shocks in demand and opportunity costs.

We report our results in Appendix Table A11. 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 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 offshorable?

This section presents two measures of 'offshorability' that intend to capture whether an occupation can be performed by a worker from abroad. While existing measures typically hinge on subjective judgments on how to classify the different attributes of a job (Blinder and Krueger 2013), our measure uses data on the prevalence of cross-border contracts in an occupation. We present evidence on the relationship between the offshorability of a job and the cross-country wage dispersion within an occupation.

5.1 Measuring offshorability

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

[18] 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.

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 offshorability of an occupation as the probability that a US employer chooses to offshore a contract in that occupation.

To construct our first measure of offshorability at the occupation level, we assign the jobs in the job-level data to occupations listed in the worker's profile. For each of the 91 occupations in the data, we compute a measure of offshorability as the share of US jobs performed by non-US workers:

$$\mathcal{O}_1^j = \frac{\text{jobs in } j \text{ where cty. employer=US and cty. worker} \neq \text{US}}{\text{All jobs in } j \text{ where cty. employer=US}}. \tag{21}$$

Our measure $\mathcal{O}_1^j$ 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.

One caveat with our measure $\mathcal{O}_1^j$ is that workers in our data can be listed under more than one occupation. In computing equation (21), we assign jobs performed by workers listed in multiple occupations to all listed occupations.[19] An alternative to this approach is to use the newer wave of the worker-level data that we collected in March 2021. Due to changes in the platform, in the March 2021 data, workers are uniquely assigned to one of 148 occupations. Unfortunately, these data cannot be merged to the job-level data collected in 2020, so that we observe the location of the worker but not that of the employer. Given these limitations, we proxy the share of offshored jobs in an occupation by the share of non-US workers in the occupation, that is:

$$\mathcal{O}_2^j = \frac{\text{Non-US workers in } j}{\text{All workers in } j}. \tag{22}$$

The logic behind this proxy is that, as noted in Section 2, only 3% of non-US workers work for domestic employers. Based on this, $\mathcal{O}_2^j$ assumes that all non-US workers only performed jobs that are being offshored. In contrast, US workers work primarily for US employers (only 25% of the jobs performed by US workers are offshored). $\mathcal{O}_2^j$ assumes

[19]That is, a job done by a worker that is listed both under 'editing' and 'translation', is counted in $\mathcal{O}_1^j$ for $j=$'Proofreaders & Editors' and for $j=$'Technical Translation'.

that none of the jobs performed by US workers are offshored. A clear advantage of measure $\mathcal{O}_1^j$ over $\mathcal{O}_2^j$ is that we do not need to make any assumptions on which jobs are offshored. The advantage of $\mathcal{O}_2^j$ is that workers are only listed in one occupation and that the disaggregation of the occupations is finer. Appendix Figure A.8 plots the two measures for the 91 narrow occupations that are available both in the job-level and in the worker-level data. It shows that the two measures are very strongly correlated across these 91 categories.

5.2 Results

Table 4 reports our two offshorability measures for most and least offshorable 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 in the degree of offshorability 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.

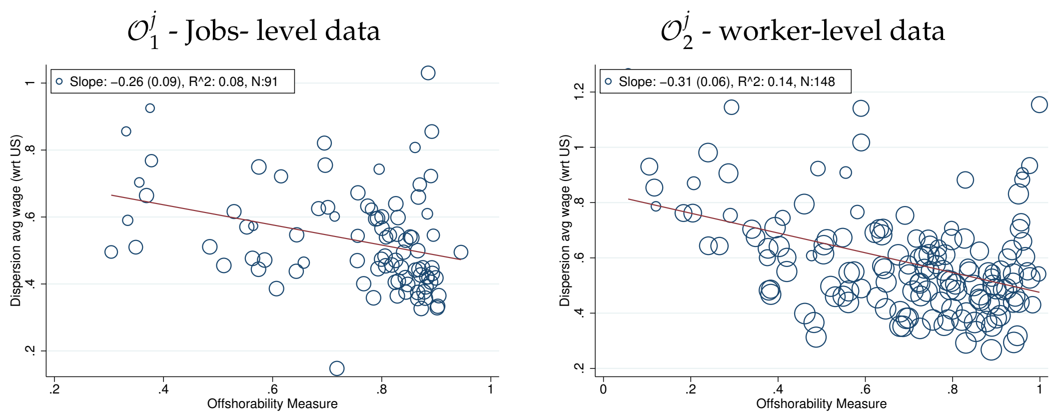
Table 4: Most and least offshorable occupations

Top 5 Occupations	$\mathcal{O}_1^j$	$\mathcal{O}_2^j$
ERP / CRM Implementation Specialists	0.95	0.96
Mobile Developers	0.90	0.92
Interior Designers	0.90	0.93
Medical Translators Professionals	0.90	0.93
Motion Graphics Freelancers	0.89	0.93
Bottom 5 Occupations		
Grant Writers	0.30	0.41
Corporate Law Professionals & Consultants	0.33	0.39
Contract Law Freelancers	0.33	0.39
Resumes & Cover Letters Writers	0.35	0.44
Paralegal Professionals	0.36	0.52

Notes: The Table reports the measures defined in equations (21) and (22) for the Top 5 and Bottom 5 occupations in terms of $\mathcal{O}_1^j$.

Offshorability and wage dispersion: Figure 7 plots our measures of offshorability (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 offshorable occupations. This result provides direct evidence that the degree of offshorability can play an important role in equalizing remote wages across countries, even though the differences remain large today.

Figure 7: Offshorability and wage dispersion

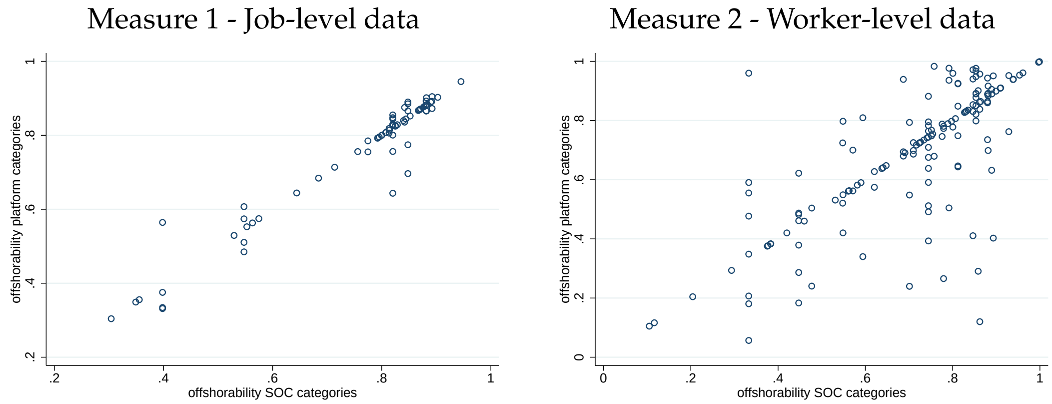


Notes: Each circle represents an occupation. The figures compares the measures in equations (21) (left panel) and (22) (right panel) to the dispersion in average wages across countries in each occupation. Circle sizes represent the number of countries with workers in the occupation.

Offshorability 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 measures 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 offshorability measure of each SOC category based on the two procedures described above. Appendix Table A.3 lists the concordance between the occupation categories in the platform and the SOC, along with the corresponding offshorability measures.

Figure 8 plots the two measures of offshorability 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.3), 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 offshorability measures are positively correlated, the SOC categories are often too broad and mask substantial heterogeneity in offshorability. For example, the SOC category 'Lawyers' includes all the legal categories in the platform, some of which are highly offshorable ('International law', which has $\mathcal{O}_2^j = 0.94$) and some of which are not offshorable ('Tax law', which has $\mathcal{O}_2^j = 0.06$). In fact, we show that the variation in offshorability within SOC categories is 0.36 of the total variation in offshorability, and 0.54 across the BLS categories that cover more than one occupation. This also suggests that having more disaggregated job categories than those currently available in official statistics can help to capture better the degree of offshorability and other important dimensions of international labor transactions.

Figure 8: Offshorability within SOC categories



Notes: Each circle represents an occupation. The left panel compares the offshorabilty of the SOC categories to platform categories computed using equation (21). The right panel compares the offshorabilty of the SOC categories to platform categories computed using equation (22).

6 Conclusion

Our 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 strickingly 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.

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A.1 Additional Tables and Figures

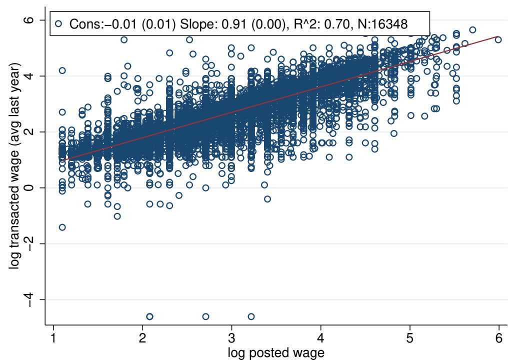
Table A1: List of Occupations

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		

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.

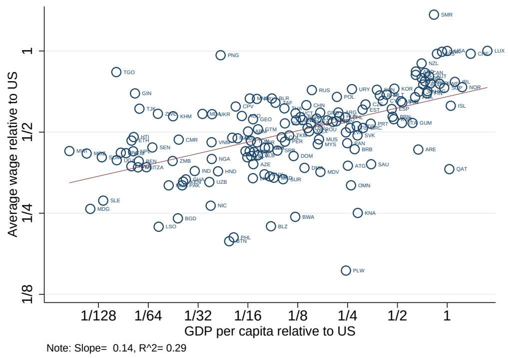
Table A3: Variance decomposition of wages

	Ask wages	Transacted wages
Var(Controls)	0.03	0.08
Var(Sector)	0.11	0.10
Var(Country)	0.26	0.34
Residual	0.45	0.41
2Cov(Country-controls)	0.03	-0.02
2Cov(Country-sector)	0.09	0.07
2Cov(Sector-controls)	0.02	0.02

Notes: The Table reports the variance decomposition of equation (2). The second and third columns show the results using ask wages from the worker-level data and transacted wages from the job-level data, respectively.

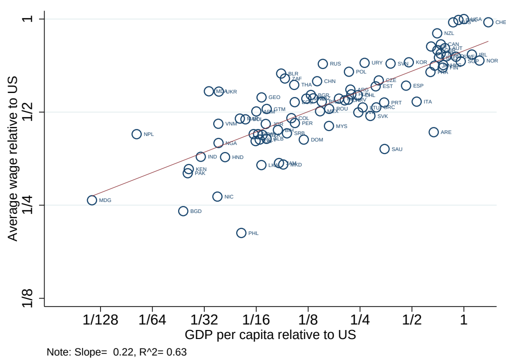
Figure A.2: Ask wages and GDP per capita relative to the US: alternative samples

(a) All countries: Raw data



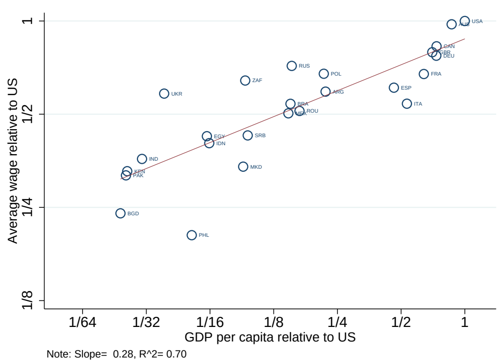
(b) All countries: With Controls

(c) Countries w/50+ workers: Raw data

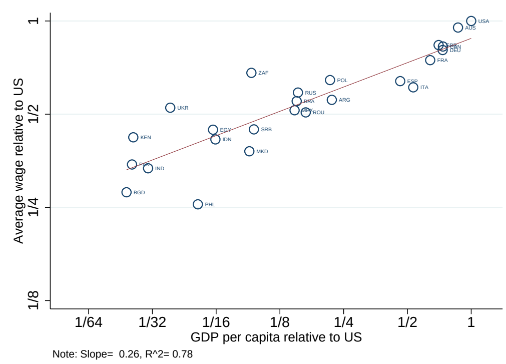


(d) Countries w/50+ workers: With Controls

(e) Countries w/500+ workers: Raw data



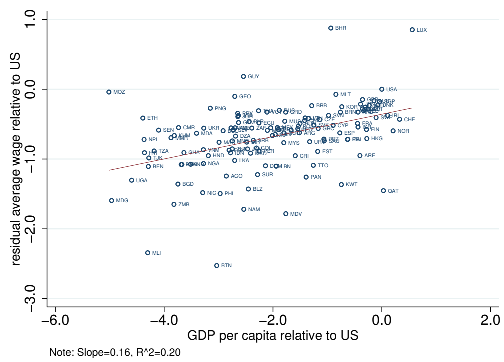
(f) Countries w/500+ workers: With Controls



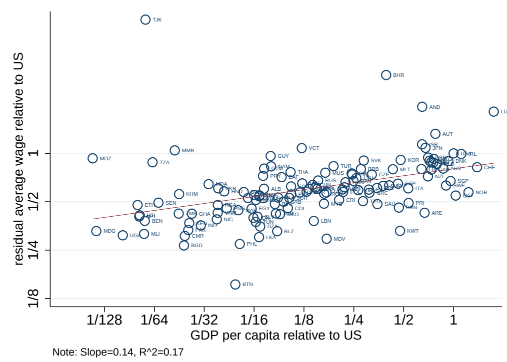
Notes: The x-axis reports the (log of) the relative GDP per capita in US dollars, taken from the World Development Indicators (WDI) collected by the World Bank. Panels on the left-hand side report the (log of) the average ask wage in country *c* relative to the US. Panels on the right-hand side reports the average relative ask wage in country *c* estimated from equation (1). Panels (a) and (b) report the estimates for all countries. Panels (c) and (d) report the estimates for the set of countries that have at least 50 workers. Panels (e) and (f) report the estimates for the set of countries that have at least 500 workers.

Figure A.3: Transacted wages and GDP per capita relative to the US: alternative samples

(a) All countries: Raw data



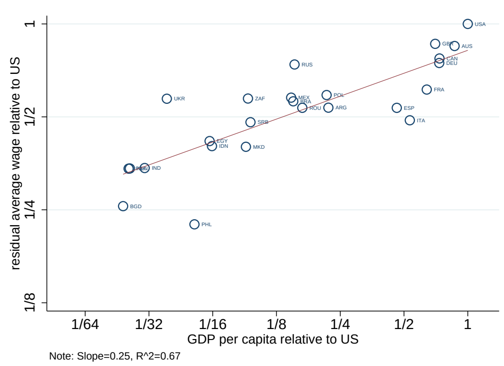
(b) All countries: With Controls



(c) Countries w/50+ workers: Raw data

(d) Countries w/50+ workers: With Controls

(e) Countries w/500+ workers: Raw data

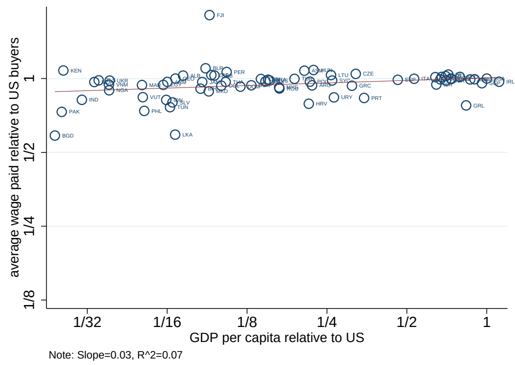


(f) Countries w/500+ workers: With Controls

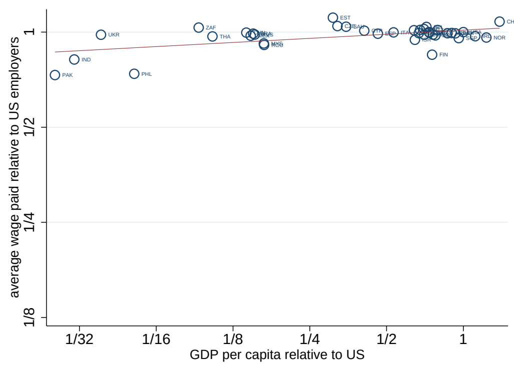
Notes: The x-axis reports the (log of) the relative GDP per capita in US dollars, taken from the World Development Indicators (WDI) collected by the World Bank. Panels on the left hand side report the (log of) the average transacted wage in country c relative to the US. Panels on the right hand side reports the average relative transacted wage in country c estimated from equation (2). Panels (a) and (b) report the estimates for all countries. Panels (c) and (d) report the estimates for the set of countries that have at least 50 workers in the worker-level data. Panels (e) and (f) report the estimates for the set of countries that have at least 500 workers in the worker-level data.

Figure A.4: Wages paid by employers from different countries and GDP per capita: alternative samples

(a) Countries w/100+ workers in worker-level data

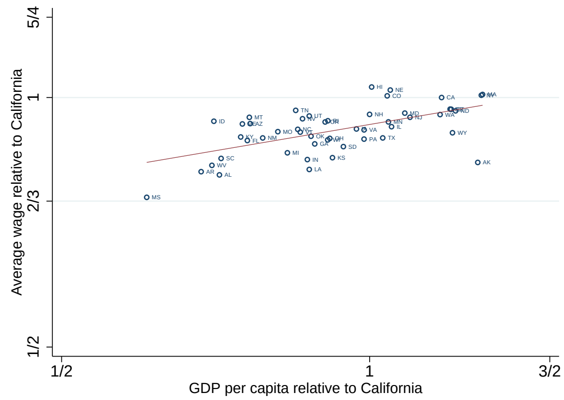


(b) Countries w/100+ employers in job-level data



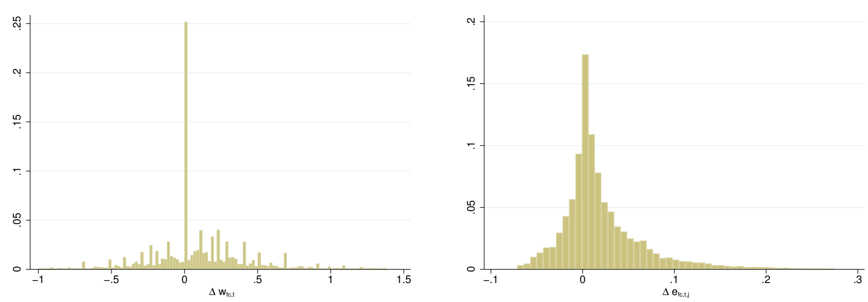
Notes: The x-axis reports the (log of) the relative GDP per capita in US dollars, taken from the World Development Indicators (WDI) collected by the World Bank. The y-axis reports relative wages estimated according to equation (3).

Figure A.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 (1) with the worker-level data. The red lines show the linear fit of the data. The estimated slope is 0.21 (0.05) and the R^2 is 0.35.

Figure A.6: Distribution of wage and exchange rate changes: transacted wages



(a) Wage changes (b) Exchange rate changes

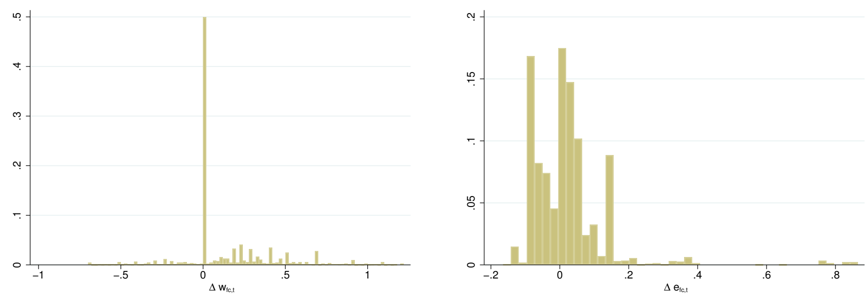
Notes: Panel (a) reports the distribution of hourly wage changes in between subsequent hourly jobs in the job-level data. Panel (b) reports the distribution of exchange rate changes for each time-spell in between subsequent jobs. The figure shows the variation in these variables behind the estimation of equation (16).

Table A4: 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.

Figure A.7: Distribution of wage and exchange rate changes: ask wages



(a) Wage changes (b) Exchange rate changes

Notes: Panel (a) reports the distribution of hourly wage changes between January-February 2019 and October-November 2019 in the worker-level data. Panel (b) reports the distribution of exchange rate changes during the same period. The figure shows the variation in these variables behind the estimation of equation (20).

Table A5: Frequency of ask wage changes

Sample	Freq. Wage Changes	Share Wage Increases	Med. Wage Increase	Med. Wage Decrease
All	0.51	0.80	0.34	-0.29

Notes: The Table presents summary statistics about the distribution of ask wage changes between January-February 2019 and October-November 2019 in the worker-level data.

Table A6: Pass-through to transacted wages: first stage regression

	(1)	(2)
	$\Delta_s w_t$	$\Delta_s w_t$
$\Delta_s e_{ct}$	0.012***	
	(0.003)	
$\pi_{c,t-s,t}$	0.008	
	(0.006)	
$\pi_{c,t-s,t} + \Delta_s e_{ct}$		0.012***
		(0.003)
$\Delta_s e_t$	-0.008	-0.008
	(0.025)	(0.025)
$\pi_{t-s,t}$	1.342***	1.337***
	(0.102)	(0.102)
Observations	108529	108529
R-squared	0.95	0.95

Notes: The table reports the first stage corresponding to columns 5 and 6 in Table (3). Country-specific linear trends are included but not reported. Standard errors are clustered at the time-spell level. *: significant at the 10% level, **: significant at the 5% level, *** significant at the 1% level.

Table A7: Pass-through to transacted wages: sample with non-zero wage changes

	(1) $\Delta_s w_{i,t}^c$	(2) $\Delta_s w_{i,t}^c$	(3) $\Delta_s w_{i,t}^c$	(4) $\Delta_s w_{i,t}^c$	(5) $\Delta_s w_{i,t}^c$	(6) $\Delta_s w_{i,t}^c$
$\Delta_s e_{ct}$	0.202***		0.219***		0.222***	
	(0.076)		(0.035)		(0.038)	
$\pi_{c,t-s,t}$	0.157		0.068		0.132	
	(0.178)		(0.091)		(0.099)	
$\pi_{c,t-s,t} + \Delta_s e_{ct}$		0.204***		0.224***		0.233***
		(0.076)		(0.036)		(0.034)
$\Delta_s w_t$			0.951***	0.938***	0.718***	0.467**
			(0.074)	(0.073)	(0.275)	(0.192)
Observations	81392	81386	81876	81876	81870	81870
R-squared	0.083	0.083	0.040	0.040	0.0029	0.039
Test $\beta_1 = \beta_2$	0.78		0.073		0.32	
Test $\beta_1 + \beta_3 = 1$			0.040	0.049	0.83	0.12
F stat 1st stage					120.2	5145.4
Specification	OLS	OLS	OLS	OLS	2SLS	2SLS

Notes: The table reestimates the specifications in Table 3 using the sample of non-zero wage changes. Country-specific linear trends are included but not reported. Columns 1-2 also include time-spell specific fixed effects and clustered standard errors at the country level. Columns 3-6 cluster standard errors at the time-spell level. *: significant at the 10% level, **: significant at the 5% level, *** significant at the 1% level.

Table A8: Pass-through to transacted wages: leave-one-out wage index

	(1)	(2)	(3)	(4)	(5)	(6)
	$\Delta_s w^c_{i,t}$	$\Delta_s w^c_{i,t}$	$\Delta_s w^c_{i,t}$	$\Delta_s w^c_{i,t}$	$\Delta_s w^c_{i,t}$	$\Delta_s w^c_{i,t}$
$\Delta_s e_{ct}$	0.179***		0.183***		0.185***	
	(0.065)		(0.029)		(0.029)	
$\pi_{c,t-s,t}$	0.110		0.077		0.086	
	(0.138)		(0.074)		(0.079)	
$\pi_{c,t-s,t} + \Delta_s e_{ct}$		0.182***		0.186***		0.189***
		(0.065)		(0.029)		(0.029)
$\Delta_s w_{-i,t}$			0.612***	0.604***	0.542***	0.467**
			(0.060)	(0.060)	(0.196)	(0.183)
Observations	108068	108068	108529	108529	108529	108529
R-squared	0.082	0.082	0.040	0.040	0.040	0.040
Test $\beta_1 = \beta_2$	0.57		0.12		0.18	
Test $\beta_1 + \beta_3 = 1$			0.0023	0.0017	0.16	0.061
F stat 1st stage					106.4	106.7
Specification	OLS	OLS	OLS	OLS	2SLS	2SLS

Notes: The table reestimates the specifications in Table 3 replacing the baseline wage index $\Delta_s W_t$ for the leave-one-out wage index $\Delta_s W_{-i,t} \equiv \sum_{l \neq i} \frac{s_{lt}}{1-s_{it}} \Delta_s w_{lt} = [\Delta_s W_t - s_{it} \Delta_s w_{it}] / [1 - s_i]$. This alternative specification alleviates the concern 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. Country-specific linear trends are included but not reported. Standard errors are clustered at the country level in columns 1 and 2, and at the time-spell level in columns 3-6. level. *: significant at the 10% level, **: significant at the 5% level, *** significant at the 1% level.

Table A9: Pass-through to transacted wages: leave-one-out wage index - first stage regression

	(1)	(2)
	$\Delta_s w_{-i,t}$	$\Delta_s w_{-i,t}$
$\Delta_s e_{ct}$	0.012***	
	(0.003)	
$\pi_{c,t-s,t}$	0.007	
	(0.006)	
$\pi_{c,t-s,t} + \Delta_s e_{ct}$		0.012***
		(0.003)
$\Delta_s e_t$	0.005	0.005
	(0.025)	(0.025)
$\pi_{t-s,t}$	1.379***	1.374***
	(0.103)	(0.102)
Observations	108529	108529
R-squared	0.95	0.95

Notes: The table reports the first stage corresponding to columns 5 and 6 in Table A8. Country-specific linear trends are included but not reported. Standard errors are clustered at the time-spell level. *: significant at the 10% level, **: significant at the 5% level, *** significant at the 1% level.

Table A10: Pass-through to transacted wages: country-level trends

	(1)	(2)	(3)	(4)	(5)	(6)
	$\Delta_s w^c_{i,t}$	$\Delta_s w^c_{i,t}$	$\Delta_s w^c_{i,t}$	$\Delta_s w^c_{i,t}$	$\Delta_s w^c_{i,t}$	$\Delta_s w^c_{i,t}$
$\Delta_s e_{ct}$	0.146	0.140***	0.143***	0.178**	0.162***	0.169***
	(0.107)	(0.029)	(0.029)	(0.070)	(0.029)	(0.029)
$\pi_{c,t-s,t}$	0.108	0.044	0.053	0.176	0.079	0.113
	(0.210)	(0.055)	(0.055)	(0.139)	(0.071)	(0.076)
$\Delta_s w_t$		0.827***	0.644***		0.839***	0.605***
		(0.061)	(0.195)		(0.060)	(0.209)
$\Delta_s T$		-0.000	0.001			
		(0.001)	(0.002)			
Observations	107099	107602	107602	107099	107602	107602
R-squared	0.073	0.031	0.031	0.10	0.062	0.0027
Test $\beta_1 = \beta_2$	0.80	0.023	0.036	0.99	0.20	0.42
Test $\beta_1 + \beta_3 = 1$		0.62	0.27		0.98	0.28
F stat 1st stage			97.7			85.8
Specification	OLS	OLS	2SLS	OLS	OLS	2SLS
Country-spell FE	no	no	no	yes	yes	yes

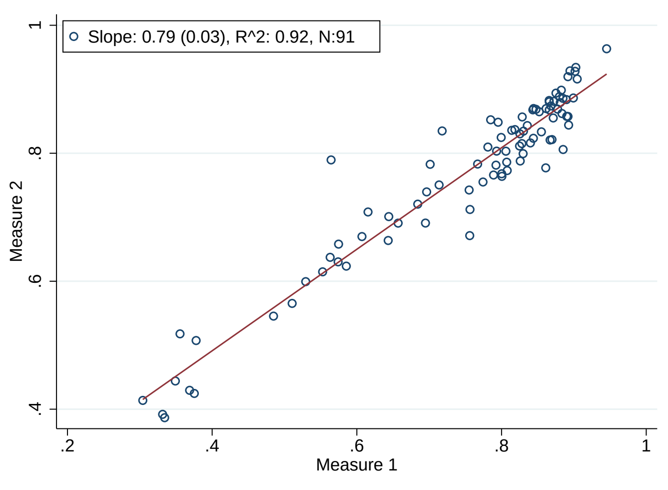
Notes: Columns 1-3 reestimate the specification in Columns 1, 3, and 5 of Table 3 without controlling for country-specific trends. Columns 4-6 reestimate the specification in Columns 1, 3, and 5 of Table 3 using the interaction between country fixed effects and spell-length fixed effects to flexibly control for (possibly non-linear) country-specific trends. Standard errors are clustered at the country level in columns 1 and 4, and at the time-spell level in columns 2, 3, 5, and 6. *: significant at the 10% level, **: significant at the 5% level, *** significant at the 1% level.

Table A11: Wage changes and international shocks: worker-level data

	(1)	(2)	(3)	(4)	(5)	(6)
	Δw_i	Δw_i	Δw_i	Δw_i	Δw_i	Δw_i
Δe_c	0.084***		0.081***		0.081***	
	(0.028)		(0.015)		(0.015)	
$\Delta \pi_c$	0.095		0.091***		0.092***	
	(0.086)		(0.031)		(0.032)	
$\Delta(\pi_c + e_c)$		0.085***		0.082***		0.082***
		(0.029)		(0.016)		(0.016)
Δw_j			1.007***	1.004***	1.055***	1.032***
			(0.012)	(0.008)	(0.054)	(0.020)
Observations	226559	226559	226559	226559	226559	226559
R-squared	0.0029	0.0029	0.0029	0.0029	0.0029	0.0029
Test $\beta_1 = \beta_2$	0.90		0.67		0.000066	
Test $\beta_1 + \beta_3 = 1$			0.000082	0.000023	0.028	0.00011
F stat 1st stage					5.65	5.65
Specification	OLS	OLS	OLS	OLS	2SLS	2SLS

Notes: The table reports the results from estimating equation (20). Standard errors are clustered at the country level. *: significant at the 10% level, **: significant at the 5% level, *** significant at the 1% level.

Figure A.8: Comparing offshorability measures



Notes: The figure compares the results of equations (21) and (22) for the 91 narrow occupations that appear both in the January 2019 and March 2020 datasets.

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 A12 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 A12: 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 (14) and (15)

The change in worker's i wage is:

$$dw_{it} = d\omega_{ct} + dz_{it}, \tag{A.3.1}$$

where the change in wages per efficiency units is given by

$$d\omega_{ct} = \frac{\theta}{\rho+\theta} db_{ct} + \frac{1}{\rho+\theta} d\varphi_{ct} + \frac{\rho-\chi}{\rho+\theta} p_t. \tag{A.3.2}$$

Differentiating (6) yields

$$dp_t = \frac{1}{1-\rho} da_t + d\omega_t,$$

which can be rewritten as

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

Substituting (13) into (13) and (13) yields:

$$d\omega_{ct} = \frac{\theta}{\rho+\theta}\left[de_{ct} + \pi_{ct}\right] + \frac{1}{\rho+\theta}\left[d\varphi_{ct} + \theta\gamma_{ct}\right] + \frac{\rho-\chi}{\rho+\theta} p_t + \frac{1}{\rho+\theta} d\phi_t.$$
$$dp_t = \frac{\theta}{\theta+\chi}\left[de_t + \pi_t\right] + \frac{1}{\theta+\chi}\left[\theta\gamma_t + d\varphi_t + d\phi_t + \frac{\rho+\theta}{1-\rho} da_t\right]$$

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

$$\begin{aligned} dp_t &= \frac{1}{1-\rho} da_t + \sum_c s_{ct_0}\mathbb{E}_c\left[d\omega_{ct} + dz_{it}\right] - dz_t. \\ &= \frac{1}{1-\rho} da_t - dz_t + \sum_c s_{ct_0}\mathbb{E}_c\left[dw_{it}\right]. \end{aligned}$$

Finally, we define the index of wage changes as:

$$dw_t \equiv \sum_c s_{ct_0}\mathbb{E}_c\left[dw_{it}\right].$$

Note that we can write:

$$dp_t = dw_t + \frac{1}{1-\rho} da_t - dz_t, \tag{A.3.4}$$

and

$$dw_t = \frac{\theta}{\theta+\chi}\left[de_t + \pi_t\right] + \frac{1}{\theta+\chi}\left[\theta\gamma_t + d\varphi_t + \frac{\rho-\chi}{1-\rho}da_t\right] + dz_t. \tag{A.3.5}$$

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

$$\begin{aligned}
dw_{it} &= \frac{\theta}{\rho+\theta}\left[de_{ct} + \pi_{ct}\right] + \frac{\rho-\chi}{\rho+\theta}dw_t + d\xi_{ct} + d\psi_t + dz_{it} \\
d\xi_{ct} &\equiv \frac{1}{\rho+\theta}\left[d\varphi_{ct} + \theta\gamma_{ct}\right] \\
d\psi_t &\equiv \frac{\rho-\chi}{\rho+\theta}\left[\frac{1}{1-\rho}da_t - dz_t\right]
\end{aligned}$$

and

$$\begin{aligned}
dw_t &= \frac{\theta}{\theta+\chi}\left[de_t + \pi_t\right] + d\phi_t \\
d\phi_t &= \frac{1}{\theta+\chi}\left[\theta\gamma_t + d\varphi_t + \frac{\rho+\theta}{1-\rho}da_t\right] + dz_t + \frac{1}{\rho-1}da_t.
\end{aligned}$$

Table A13: List of occupations and measure 1

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

Table A14: List of occupations and measure 2

Occupation Platform	Measure 2	SOC title	SOC code	Measure 2	Occupation Platform	Measure 2	SOC title	SOC code	Measure 2
Order Processing	1.00	Order Clerks	43-4151	1.00	Mobile App Development	0.88	Sw Developers	15-1252	0.88
Physics	1.00	Physicists	19-2012	1.00	Search Engine Optimization	0.88	Market Research Analysts and Mktg	13-1161	0.74
Building Information Modeling	0.98	Architectural and Civil Drafters	17-3011	0.76	Full-Stack Development	0.88	Web and Digital Interface Designers	15-1255	0.85
Data Extraction	0.98	Data Warehousing	15-1243	0.79	Interior Design	0.86	Interior Designers	27-1025	0.86
Game Art	0.98	Video Game Designers	15-1255	0.85	Technical Translation	0.86	Interpreters and Translators	27-3091	0.88
AR/VR Development	0.97	Special Effects Artists and Animators	27-1014	0.85	Biology	0.86	Biologists	19-1029	0.86
Mobile Design	0.97	Web and Digital Interface Designers	15-1255	0.85	Medical Translation	0.86	Interpreters and Translators	27-3091	0.88
Jewelry Design	0.96	Craft Artists	27-1012	0.96	2D Animation	0.85	Special Effects Artists and Animators	27-1014	0.85
International Law	0.96	Lawyers	23-1011	0.33	UX/UI Design	0.85	Web and Digital Interface Designers	15-1255	0.85
Prototyping	0.96	Computer Programmers	15-1251	0.80	Machine Learning	0.85	Data Scientists	15-2051	0.81
Scrum Master	0.96	Information Technology Project Managers	15-1299	0.86	Systems Engineering	0.84	Computer Systems Engineers/Architects	15-1299	0.86
Lifestyle Coaching	0.95	Training and Development	13-1152	0.95	Chemical & Process Engineering	0.84	Chemical Engineers	17-2041	0.84
Data Entry	0.95	Data Entry Keyers	43-9021	0.93	Language Tutoring	0.83	Foreign Lang. and Lit. Teachers, Pse	25-1124	0.83
Lead Generation	0.95	Mktg Managers	11-2021	0.89	3D Modeling & Rendering	0.83	Special Effects Artists and Animators	27-1014	0.85
Game Development	0.95	Video Game Designers	15-1255	0.85	Energy Engineering	0.83	Energy Engineers, Except Wind and Solar	17-2199	0.83
Language Localization	0.94	Interpreters and Translators	27-3091	0.88	Recruiting	0.83	Human Resources	13-1071	0.83
3D Animation	0.94	Special Effects Artists and Animators	27-1014	0.85	Front-End Development	0.82	Web and Digital Interface Designers	15-1255	0.85
Electronic Engineering	0.94	Electronics Engineers, Except Computer	17-2072	0.94	Editorial Design	0.81	Designers, All Other	27-1029	0.59
Logo Design	0.94	Graphic Designers	27-1024	0.69	Civil Engineering	0.81	Civil Engineering Technologists and Technicians	17-3022	0.81
Mathematics	0.94	Mathematicians	15-2021	0.94	Web Design	0.80	Web and Digital Interface Designers	15-1255	0.85
Data Engineering	0.94	Database Architects	15-1243	0.79	Accounting	0.80	Accountants and Auditors	13-2011	0.80
Data Mining	0.93	Data Scientists	15-2051	0.81	Singing	0.80	Musicians and Singers	27-2042	0.55
Online Research	0.92	Data Scientists	15-2051	0.81	Social Media Mktg	0.80	Search Mktg Strategists	13-1161	0.74
Desktop Sw Development	0.92	Sw Developers	15-1252	0.88	Social Media Strategy	0.79	Public Relations	27-3031	0.70
TeleMktg	0.91	Telemarketers	41-9041	0.91	Architecture	0.79	Architects, Except Landscape and Naval	17-1011	0.79
Customer Service	0.91	Customer Service Representatives	43-4051	0.91	Systems Administration	0.79	Network and Computer Systems Admin	15-1244	0.78
Back-End Development	0.91	Database Admin	15-1242	0.89	Sales & Business Development	0.78	Search Mktg Strategists	13-1161	0.74
Automation Testing	0.90	Sw Quality Assurance Analysts and Testers	15-1253	0.86	Illustration	0.78	Fine Artists	27-1013	0.78
Tech Support	0.90	Computer User Support	15-1232	0.90	Scripting & Automation	0.78	Computer Programmers	15-1251	0.80
DevOps Engineering	0.89	Sw Developers	15-1252	0.88	Cartoons & Comics	0.77	Fine Artists	27-1013	0.78
Mobile Game Development	0.89	Video Game Designers	15-1255	0.85	Network Security	0.77	Information Security Analysts	15-1212	0.75
CMS Development	0.89	Web and Digital Interface Designers	15-1255	0.85	Search Engine Mktg	0.76	Search Mktg Strategists	13-1161	0.74
Landscape Architecture	0.89	Landscape Architects	17-1012	0.89	Data Processing	0.76	Data Entry Keyers	43-9021	0.93
Translation	0.89	Interpreters and Translators	27-3091	0.88	Video Editing	0.75	Film and Video Editors	27-4032	0.75

Table A15: List of occupations and measure 2 (cont.)

Occupation Platform	Measure 2	SOC title	SOC code	Measure 2	Occupation Platform	Measure 2	SOC title	SOC code	Measure 2
Deep Learning	0.75	Data Scientists	15-2051	0.81	Financial Mgmt./CFO	0.59	Treasurers and Controllers	11-3031	0.59
Information Security	0.75	Information Security Analysts	15-1212	0.75	A/B Testing	0.58	Sw and Web Dev, Prgmr, and Testers	15-1250	0.58
Network Administration	0.75	Network and Computer Systems Admin	15-1244	0.78	Videography	0.57	Producers and Directors	27-2012	0.62
Emerging Tech	0.74	Search Mktg Strategists	13-1161	0.74	Financial Analysis & Modeling	0.56	Financial and Investment Analysts	13-2051	0.56
Project Mgmt.	0.74	Project Mgmt.	13-1082	0.74	Presentation Design	0.56	Art Directors	27-1011	0.57
Legal Translation	0.74	Interpreters and Translators	27-3091	0.88	Technical Writing	0.56	Technical Writers	27-3042	0.56
Business Analysis	0.73	Business Continuity Planners	13-1199	0.73	Immigration Law	0.56	Lawyers	23-1011	0.33
Campaign Mgmt.	0.73	Advertising and Promotions Managers	11-2011	0.73	Voice Talent	0.55	Musicians and Singers	27-2042	0.55
Transcription	0.73	Audio and Video Technicians	27-4011	0.71	Community Mgmt.	0.55	Public Relations	27-3031	0.70
Product & Industrial Design	0.72	Commercial and Industrial Designers	27-1021	0.72	Fashion Design	0.53	Fashion Designers	27-1022	0.53
Music Composition	0.72	Music Directors and Composers	27-2041	0.55	Music Production	0.52	Music Directors and Composers	27-2041	0.55
Sourcing & Procurement	0.72	Purchasing Managers	11-3061	0.72	Brand Strategy	0.51	Market Research Analysts and Mktg	13-1161	0.74
Chemistry	0.72	Chemists	19-2031	0.72	Database Development	0.50	Database Architects	15-1243	0.79
Digital Mktg	0.71	Search Mktg Strategists	13-1161	0.74	Local Photography	0.50	Photographers	27-4021	0.48
Art Direction	0.70	Art Directors	27-1011	0.57	User Research	0.49	Market Research Analysts and Mktg	13-1161	0.74
Firmware Development	0.70	Sw Developers	15-1252	0.88	Creative Writing	0.49	Poets, Lyricists and Creative Writers	27-3043	0.45
Audio Production	0.70	Audio and Video Technicians	27-4011	0.71	Copywriting	0.48	Writers and Authors	27-3043	0.45
Brand Identity Design	0.69	Graphic Designers	27-1024	0.69	Regulatory Law	0.48	Lawyers	23-1011	0.33
Bookkeeping	0.69	Bookkeeping, Accounting, and Auditing Clerks	43-3031	0.69	Content Writing	0.46	Poets, Lyricists and Creative Writers	27-3043	0.45
Audio Editing	0.69	Audio and Video Technicians	27-4011	0.71	Training & Development	0.46	Training and Development	13-1151	0.46
Graphic Design	0.68	Graphic Designers	27-1024	0.69	Musician	0.42	Musicians and Singers	27-2042	0.55
CAD	0.68	Architectural and Civil Drafters	17-3011	0.76	Mgmt. Consulting	0.42	Mgmt. Analysts	13-1111	0.42
Market Research	0.68	Market Research Analysts and Mktg	13-1161	0.74	AR/VR Design	0.41	Special Effects Artists and Animators	27-1014	0.85
Mechanical Engineering	0.65	Mechanical Engineers	17-2141	0.65	Content Strategy	0.40	Mktg Managers	11-2021	0.89
Data Analytics	0.65	Data Scientists	15-2051	0.81	Mktg Strategy	0.39	Market Research Analysts and Mktg	13-1161	0.74
Data Visualization	0.64	Data Scientists	15-2051	0.81	Editing & Proofreading	0.38	Editors	27-3041	0.38
Electrical Engineering	0.64	Electrical Engineers	17-2071	0.64	Structural Engineering	0.38	Civil Engineers	17-2051	0.38
Email Mktg	0.64	Search Mktg Strategists	13-1161	0.74	Ghostwriting	0.38	Writers and Authors	27-3043	0.45
HR Administration	0.64	Human Resources Workers	13-1070	0.64	Logistics & Supply Chain Mgmt.	0.38	Logistics Analysts	13-1081	0.38
Database Administration	0.63	Database Admin	15-1242	0.89	Paralegal	0.38	Paralegals and Legal Assistants	23-2011	0.38
Video Production	0.63	Producers and Directors	27-2012	0.62	Business & Corporate Law	0.35	Lawyers	23-1011	0.33
Creative Direction	0.62	Poets, Lyricists and Creative Writers	27-3043	0.45	Instructional Design	0.34	Designers, All Other	27-1029	0.59
Mktg Automation	0.59	Market Research Analysts and Mktg	13-1161	0.74	Tax Preparation	0.29	Tax Preparers	13-2082	0.29
General Counsel	0.59	Lawyers	23-1011	0.33	IT Compliance	0.29	Sw Quality Assurance Analysts and Testers	15-1253	0.86

Table A16: List of occupations and measure 2 (cont.)

Occupation Platform	Measure 2	SOC title	SOC code	Measure 2	Occupation Platform	Measure 2	SOC title	SOC code	Measure 2
Business Writing	0.29	Writers and Authors	27-3043	0.45	Scriptwriting	0.18	Writers and Authors	27-3043	0.45
Fine Art	0.27	Fine Artists	27-1013	0.78	Labor & Employment Law	0.18	Lawyers	23-1011	0.33
Product Photography	0.24	Photographers	27-4021	0.48	Knowledge Representation	0.12	Computer Systems Engineers/Architects	15-1299	0.86
Public Relations	0.24	Public Relations	27-3031	0.70	Acting	0.12	Actors	27-2011	0.12
Intellectual Property Law	0.21	Lawyers	23-1011	0.33	Grant Writing	0.10	Fundraisers	13-1131	0.10
Career Coaching	0.20	Educational, Guidance, and Career Adv	21-1012	0.20	Tax Law	0.06	Lawyers	23-1011	0.33