Using Online Data for International Wage Comparisons

Alberto Cavallo
Javier Cravino
Andres Drenik

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Alberto Cavallo
Harvard Business School

Javier Cravino
University of Michigan

Andres Drenik
Columbia University

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Alberto Cavallo
Harvard Business School
and NBER

Javier Cravino
University of Michigan
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Andres Drenik
Columbia University

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Abstract

We use a novel dataset from a large freelance website to document international wage differences for performing tasks that can be delivered online. The data records detailed information on tasks and worker characteristics which facilitates cross-country comparisons. We show large wage disparities across freelancers from different countries working on narrowly defined tasks. These wage differentials across countries are not driven by differences in observable worker characteristics. Real exchange rate levels account for about 50 percent of the cross-country-variation in average wages, and the elasticity of relative wages with respect to the real exchange rate is about 0.4. The magnitudes of these findings are pervasive across different country groups and types of jobs.

Keywords: International Comparisons, Real Exchange Rates, Wages, PPP.

JEL Codes: F31, F41, F62

*Email: acavallo@hbs.edu, jcravino@umich.edu, ad3376@columbia.edu. We thank seminar participants at the University of Gronnigen and the SED Summer Meetings for helpful comments and suggestions.

1 Introduction

Understanding differences in wages across countries is central to the study both of International and Development Economics. It is well documented that wages differ dramatically across countries and are higher in countries with higher GDP per capita. These differences in wages can arise from cross-country differences in technology, capital, or workers' skills. Disentangling the contribution of each of these factors using national wage surveys is difficult, since in these datasets workers' firms of employment and workers' characteristics (skills, occupations, etc.) are not directly comparable across countries.

This paper uses a new cross-country dataset on individual-level wages obtained from a large freelance website to disentangle the sources of cross-country wage differentials. These data provide three key advantages over existing wage surveys. First, in the website, freelancers from around the world apply to the same jobs and are hired to perform narrowly-defined tasks. Thus, 'occupations' in our data are identical and directly comparable across the countries in our sample. Second, the set of tasks that are contracted through the platform are easily traded, can be delivered online, and typically do not require much capital other than access to a computer. Finally, the dataset contains detailed and standardized information on worker characteristics, which again can be easily compared around the globe. For instance, the dataset contains results for over 200 standardized test that are taken online, and information on freelancers' experience, past earnings, and quality ratings. Thus, compared to other labor markets, this is a labor market in which: i) previously studied factors leading to unequal wages (such as mobility costs, differences in firms' productivity and capital, etc.) should be less prevalent and, ii) it is easier to analyze the wages of more homogeneous group of workers.

We use these data to document wage differentials across comparable workers located in different countries. We first show that wages are strongly correlated with aggregate price levels across countries. The slope of a regression of relative wages on relative price levels is around 0.5, showing that differences in wages are smaller than those observed for average prices. We find a similar relation between relative prices and relative wages across US states.

We then evaluate whether the observed differences in wages across countries are driven by cross-country differences in workers' skills or by differences in returns to those skills across countries. With this in mind, we conduct a 'Blinder-Oaxaca' decomposition (Blinder, 1973; Oaxaca, 1973), and measure the wage differentials that are predicted by the observed differences in skills. These predictions are uncorrelated to aggregate price levels, implying that the cross-country differences in wages are almost exclusively driven by cross-country differences in returns. In contrast, only half of the variation in wages across US states is driven by differences in returns across states.

We then document substantial differences in wage differentials across occupations. The occupations in which wages are more equalized are Engineering, Web Design, and Translation services. Arguably, these occupations are characterized by producing tasks that can be easily traded across countries. In contrast, the largest wage differentials arise in Sales, Legal, and Accounting, which may require country-specific knowledge and impose barriers of entry to foreign workers. We note, however, that wages are not equalized even in the most easily traded occupations. When decomposing wages by occupations, we find that wage differentials are -once again- mainly driven by differences in returns as opposed to differences in the skills of freelancers across countries.

Finally, we use the job history data in the platform to evaluate how wages respond to changes in the nominal exchange rate. We find that wages are rigid in US dollars, so that ERPT into local currency wages is high. In particular, we find that, in response to a 10% depreciation of the freelancers' country currency, hourly wages in US dollars fall by about1%, so that the hourly wage in local currency increases by about 9%. We find similar numbers even if we focus on a subsample of non-zero wage changes, implying that this low pass-through is not driven by stickiness in US dollar wages However, a significant difference exists in the US dollar wage response to depreciations and appreciations. On average, a 10% appreciation of the local currency increases the US dollar wage by about 6% after conditioning on a wage change.

The paper is related to a long literature on international price and wage comparisons. The main source of international price comparisons is the PWT (see Feenstra et al., 2015). A more recent literature uses online data for international price comparisons (see for example Cavallo et al., 2014 and Gorodnichenko and Talavera, 2017). Our paper is more closely related to the recent literature 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 around the globe. We contribute to this literature by providing data on wages for occupations that can be easily traded online. The data provides detailed worker characteristics that allow us to compare similar workers across countries.

The rest of the paper is organized as follows. Section 2 describes the data. Section 3 presents our main findings on differences in wages across countries. Section 4 documents how changes in exchange rate affect relative wages, and the last section concludes.

2 Data

2.1 Data description

Our wage data comes from a large freelance website. An increasing number of workers are choosing to freelance. In the US, about 57 million workers freelanced in 2018, up from 53 million in 2014. 64 percent of these freelancers found work online, a 22 percentage point increase since 2014.[1] A freelance website is a platform where freelancers and employers get matched and set the terms of the labor relationship. Our data comes from the largest freelance website in the market today.

The platform claims millions registered freelancers and clients around the globe. We focus on a subsample of 100,000 freelancers that are active and have experience in the platform. The type of work that is transacted through the website mainly involves the online delivery of tasks or services. These jobs encompass a wide range of occupations, ranging from accountants to web developers.

The platform works in the following way. Freelancers in the website post an hourly wage at which they are willing to work. Although freelancers can enter wages in their local currency, all wages in the platform are displayed in US dollars. When an employer signs in in the platform, it can post a job listing, to which freelancers can apply, or it can alternatively search for freelancers that match their needs.

A unique feature of this dataset is that, in addition to the posted wage, the platform records a number of detailed characteristics about the freelancers that are typically not available in wage surveys. Employers can observe these characteristics when searching for a freelancer online. In particular, the dataset contains the following characteristics about the freelancer:

General information: The dataset includes information on the name, city, and country of each freelancer, along with the types of jobs or "occupations" that the freelancer can perform. In addition, freelancers can post a brief written description of their skills and interests. Freelancers can also list their availability, and the platform records the average response time of each freelancer. We anonymize the dataset of all personal information, and extract a freelancer unique identifier along with their location, occupation, availability and response.

[1] "Freelancing in America 2018".

Skills: Freelancers can list a number of predetermined skills on their profile, and can also post their CVs on the platform. In addition, freelancers can take online examinations through the platform to certify their expertise in certain areas. Examples of such examinations include: "Adobe Photoshop CS4 Test" or "English To Spanish Translation Skills Test". Importantly, these tests are standardized across countries, and will be used as our main measure of skills. We observe about 200 different tests in the platform. We observe which are the tests that each freelancer has taken, along with his/her 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 freelancers around the globe.

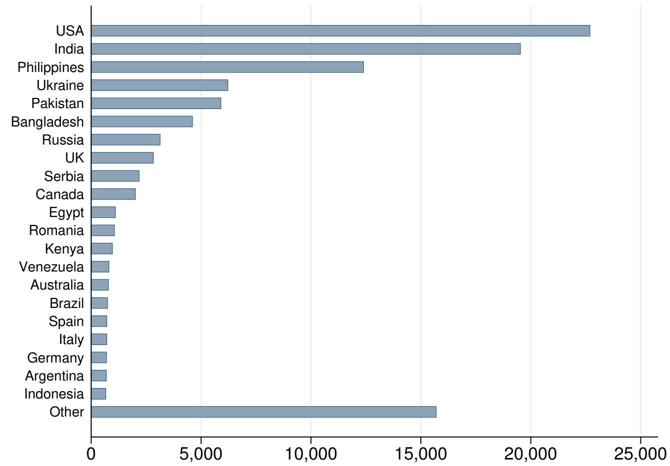
Experience and quality: The data records the total earnings, number of jobs, and number of hours worked for each freelancer on the platform. In addition, the platform reports a number of quality measures for each freelancer. It reports the 'success rate' of each freelancer, which measures the percentage of contracted jobs that the freelancer has completed. It also certifies experienced freelancers as 'Top Rated'. To earn and maintain a Top Rated status, a freelancer must at least have a completed profile, a job success score of 90%, $1,000 in earnings in the last year, and been first hired through the platform at least 90 days ago.

Job history on the platform: Finally, we also observe each freelancer's job history on the platform. For each job that the freelancer has completed, the platform reports: a description of the job, the total payment received for the job, and if the contract was stipulated on an hourly basis, the hourly rate and number of hours worked by the freelancer. It also reports the identity of the employer, along with an optional employer review of the freelancer.

2.2 Summary statistics

We begin by presenting some summary statistics on the dataset. Figure 1 shows the number of freelancers by country in our sample. Our sample has freelancers from a total of 182 countries, although as the figure shows, these freelancers are not evenly distributed across the globe. Importantly, our sample of countries includes both developed and developing countries. The countries with the most freelancers in our sample are the US, India, Philippines and Ukraine. Overall, we have 91 countries that have at least 50 freelancers, 67 that

Figure 1: Freelancers by country



Notes: The figure the number of freelancers in the largest countries in our sample.

have at least 100, and 27 that have at least 500 freelancers. In what follows we will focus on the subsample of 67 countries for which we see at least 100 active freelancers.

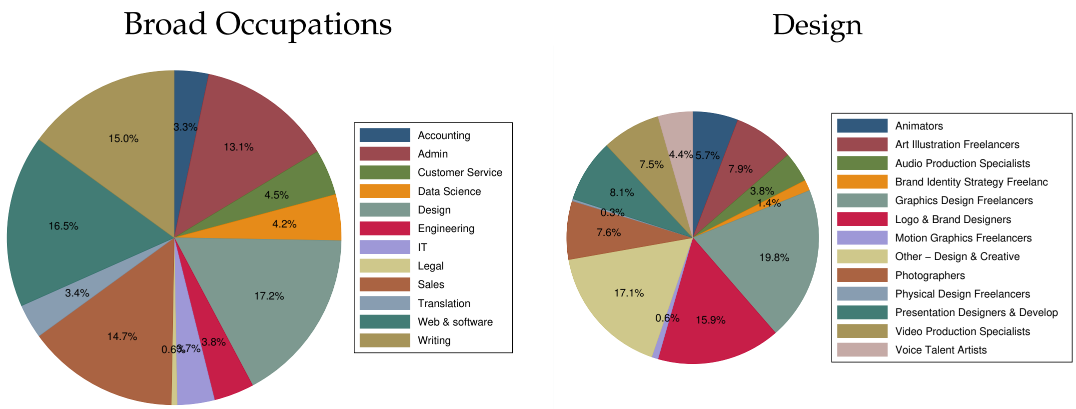
Figure 2 list the distribution of freelancers across occupations. Freelancers are grouped into 12 'Broad Occupations'. In our sample, the largest occupations in terms of number of freelancers are 'Design', 'Web and Software', and 'Sales' (containing 17.2, 16.5 and 14.7 percent of the freelancers of our sample respectively). In contrast only 0.6 percent of the freelancers in our sample are listed in 'Legal'. Each Broad Occupation can be further dissagregated into 'Detailed Occupations'. For example, the left panel of Figure 2 shows that within Design, 20 percent of freelancers are listed as 'Graphic Design'. 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, for freelancers in the US, India, China, Brazil, and the rest of the world. There is wide variation in average wages: the average hourly wage for a US freelancer is 47 dollars, which is about three times the average wage in India, and almost two times the average wage in Brazil. As we will show below, these cross-country differences in wages are closely related to cross-country differences in relative prices.

By construction, our final sample includes freelancers that have been very active in the platform.[2] In our sample, the average freelancer in the US has completed 33 jobs, worked

[2]We limit our sample to freelancers that have a detailed profile, positive earnings, and previous job experience to make sure that our data on posted wages truly reflect wages that are transacted.

Figure 2: Freelancers by occupation



Notes: The left panel reports the share of the freelancers in our sample that is listed in each of the 12 Broad Occupations. The right panel reports the share of Design freelancers in each design sub-occupation.

88 hours, and earned about 2,000 US dollars. Freelancers in India are even more active in the platform, having completed 125 jobs, worked 1,000 hours, and earned 6,000 US dollars on average.

Most freelancers in our sample are willing to work full-time, and are available either 'As needed' or 'Over 30 hours a week'. Some freelancers do seem to work part time, about 17 percent of freelancers in the US and 5 percent in India indicate that the can work less than 30 hours in a week. Finally, about 40 percent of freelancers in our sample have earned Top rated status.

2.3 Wage determinants

Before comparing wages across countries, we evaluate how the freelancers' characteristics correlate with their hourly wage by running the following OLS regression:

$$w_f = \beta X_f + D_f^c \times D_f^j + \varepsilon_f. \tag{1}$$

Here, ω_f is the log-hourly wage of freelancer f, X_f is a vector of freelancers' characteristics, containing experience variables (log-earnings, and number of jobs), skill variables (number of tests and the average score), quality ratings (Top Rated, and dummies for success rates), availability (dummies for Full/part-time, and dummies response time), and an indicator for whether the freelancer works in an agency (multi-worker, single worker). Finally, $D_f^c \times D_f^j$ denote the set of country times sector dummies.

Table 1: Summary statistics

	US	India	China	Brazil	Others
Freelancers	22,691	19,529	388	748	62,769
Median wage	35	14	22	20	17
Average wage	47	15	34	27	21
Jobs	33	125	63	36	59
Hours	88	1,002	236	383	511
Earnings	2,000	6,000	3,000	4,000	4,000
Availability:					
Not available	0.11	0.05	0.10	0.10	0.09
As needed	0.40	0.22	0.29	0.42	0.34
< 30 hours per week	0.17	0.05	0.08	0.17	0.14
> 30 hours per week	0.32	0.69	0.53	0.31	0.42
Agency	0.04	0.48	0.12	0.02	0.14
Share Top Rated	0.43	0.63	0.37	0.30	0.39

Notes: Statistics are reported for the average freelancer in each country of our sample, unless stated otherwise. 'Others' reports the statistics in the first column for the average country in our sample.

The results from this regression are reported in Table 2. The coefficient on past earnings is positive and statistically different from zero, and the coefficients on the number of jobs dummies are monotonically increasing, which indicates that more experienced freelancers earn higher wages. Hourly wages also increase with the number of test that the freelancer has taken, and with the freelancer's average score in these tests. Quality ratings also positively affect hourly wages, and Top Rated freelancers earn an hourly wage premium of 0.3 log points. In addition, the coefficients of dummies for success rates are monotonically increasing. The omitted category is a missing success-rating, indicating that freelancers with a low rating (i.e. success ratings of less than 70%) face a wage penalty, but freelancers with a 100% rating do not earn more than those with no rating.

The table also shows that freelancers that work through agencies earn on average 0.15 log point less than freelancers that work independently. This could be the result of agencies helping new freelancers find a job, in order to obtain a good reputation in the platform and become self-employed. Finally, those freelancers that tend to respond faster and that work more hours in a week tend to earn less than other freelancers. This could be explained by spontaneous freelancers being more selective when deciding which jobs to accept.

Table 2: Wage determinants

	Coef.	Std. Err.		Coef.	Std. Err.
Experience			**Quality ratings**		
Earnings	0.0656***	(0.000569)	Top rated	0.297***	(0.00227)
<=5 jobs	-0.00322	(0.00230)	SR <70%	-0.135***	(0.00767)
[6,15) jobs	0.0493***	(0.00300)	SR [70%,80%)	-0.0842***	(0.00602)
[15,50) jobs	0.0776***	(0.00472)	SR [80%,90%)	-0.0413***	(0.00416)
>=50 jobs	0.0762***	(0.0136)	SR [90%,95%)	-0.0113***	(0.00420)
			SR [95%,100%)	-0.00177	(0.00393)
Skills			SR 100%	0.00154	(0.00311)
# test	0.00248***	(0.000286)			
Av. score	0.0367***	(0.00234)	**Part time/full time**		
			As needed	0.0121	(0.0124)
Agency			<= 30 hrs/week	0.0141	(0.0125)
Single worker	-0.150***	(0.00685)	> 30 hrs/week	-0.0499***	(0.0124)
Multi worker	-0.0569***	(0.00738)			
			Response time		
			< 24 hrs	-0.188***	(0.00410)
			< 3 days	-0.0482***	(0.00259)
			3+ days	-0.0703***	(0.00688)

Notes: The table reports the coefficients estimated from equation (1). The estimation includes country-sector fixed effects.

3 International wage comparisons

This section uses our data for international wage comparisons. With this in mind, we compute relative wages between each country and the US as:

$$rer_{i,us}^{w} = w_i - w_{us}, \tag{2}$$

where

$$w_i = \frac{1}{N_i} \sum_{f \in i} w_f, \tag{3}$$

is the average log-wage across all freelancers in country i.

Figure 3 compares the distribution of these relative wages with cross-country relative price levels, which we obtain from the PWT. The figure shows that on average, differences in wages across countries are smaller and more compressed than those observed for average prices: the distribution of relative prices has a higher variance and fatter tails that the distribution of wages. Table 3 documents these patterns in detail and adds a comparison to relative GDP per capita.

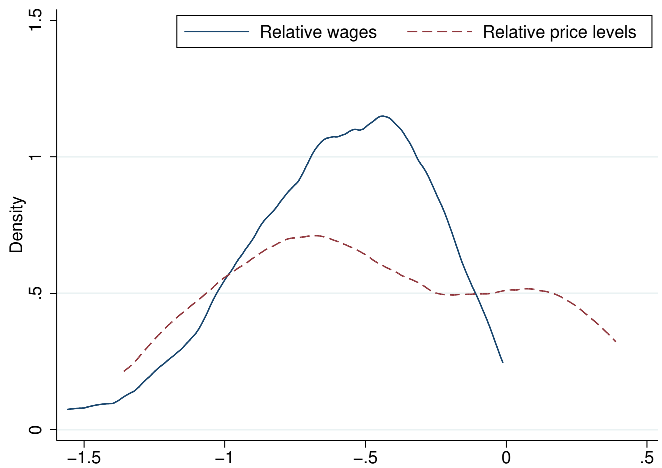
Figure 4 plots these relative wages vs cross-country relative price levels. The figure shows a very strong positive relation between relative wages and prices: Freelancers from more expensive countries earn on average higher wages. In fact, differences in relative price levels account for 42 percent of the variation in relative wages across countries. The slope of this relation is 0.44, reflecting that relative wages in our data are more equalized across countries than the aggregate price levels in the Penn World Tables (Feenstra et al., 2015).

Figure 5 compares differences in online wages and aggregate price levels across US states (we use the relative price level of output computed by the BEA). In particular, for each state s we compute the average wage relative to California, $rer_{s,ca}^{w} = w_s - w_{ca}$, using formulas analogous to (2) and (3). The figure shows that the pattern across US states is similar to the one we observe across countries: online wages and price levels are positively correlated, though differences in wages are smaller than differences in aggregate price levels. We summarize these results below:

gros

Fact 1. *Online wages are strongly correlated with aggregate price levels both across countries and across US states, but differences in online wages are smaller than those observed for average prices.*

Figure 3: Wages and price levels relative to the U.S.



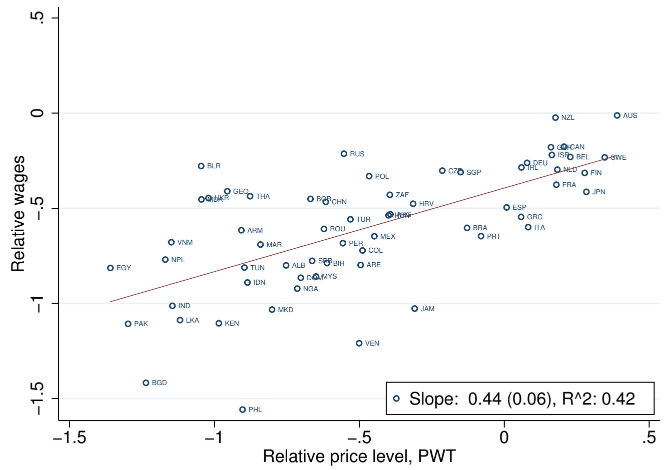
Notes: The x-axis reports the (log of) relative wages computed according to equations (2) and (3), and the price level of output computed by the PWT (variable pl_gdpo).

Table 3: Cross-country distribution of relative wages, prices, and GDP per capita

	Wages	Prices	GDP per capita
1%	-1.56	-1.36	-4.37
5%	-1.11	-1.17	-3.67
10%	-1.03	-1.12	-3.28
25%	-0.80	-0.89	-2.70
50%	-0.56	-0.52	-1.92
75%	-0.33	0.01	-0.45
90%	-0.23	0.18	-0.28
95%	-0.18	0.28	-0.11
99%	-0.01	0.39	0.11
Mean	-0.60	-0.47	-1.81
Std. Dev.	0.33	0.49	1.19

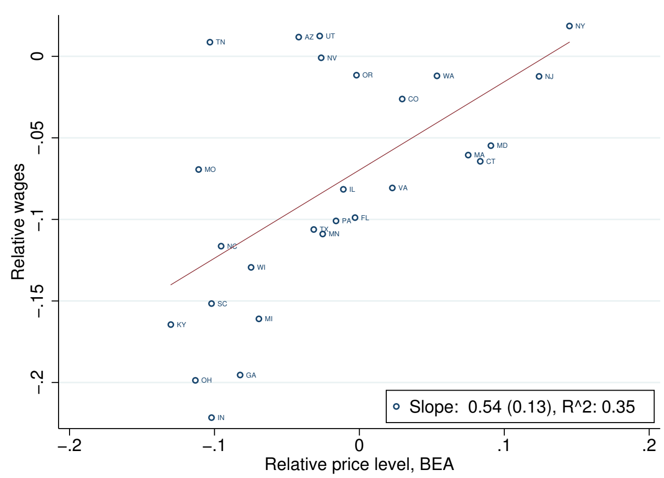
Notes: The table reports, moments of the cross-country distributions of relative wages, relative prices, and relative GDP per capita.

Figure 4: Online wages and relative price levels



Notes: The x-axis reports the (log of) the relative price level of output computed by the PWT (variable pl_gdpo). The y-axis reports relative wages computed according to equations (2) and (3).

Figure 5: Online wages and relative price levels across US states



Notes: The x-axis reports the (log of) the relative price level of output computed by the BEA. The y-axis reports relative wages relative in each state relative to the average wage in California, computed according to equations analogous to (2) and (3).

3.1 Decomposing wage differentials

We now 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 an 'Blinder-Oaxaca' decomposition (Blinder, 1973; Oaxaca, 1973) of the observed wage differentials. We start by writing the log-wage of freelancer f in country c as:

$$w_{f,c} = X'_{f,c}\beta_c + \varepsilon_{f,c}, \tag{4}$$

for $c \in (i, us)$. Here, $X'_{f,c}$ 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 i and the US can be written as:

$$rer^w_{i,us} \equiv \mathbb{E}\left(w_{f,i}\right) - \mathbb{E}\left(w_{f,us}\right) = \mathbb{E}\left(X'_{f,i}\right)\beta_i - \mathbb{E}\left(X'_{f,us}\right)\beta_{us},$$

where we used that $\mathbb{E}\left(\varepsilon_{f,c}\right) = 0$ by construction.

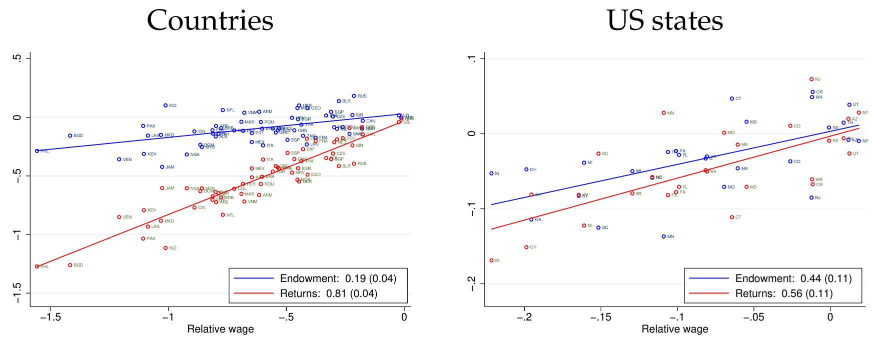
The goal of the 'Blinder-Oaxaca' decomposition is to evaluate whether observed wage differentials across countries are driven by differences in workers' characteristics $X'_{f,c}$ or by differences in the returns to those skills, β_c. With this in mind, we can re-arrange equation (4) as:

$$rer^w_{i,us} = \underbrace{\left[\mathbb{E}\left(X'_{i,c}\right) - \mathbb{E}\left(X'_{f,us}\right)\right]\beta_{us}}_{\text{Endowment}} + \underbrace{\mathbb{E}\left(X'_{i,c}\right)\left[\beta_i - \beta_{us}\right]}_{\text{Returns}}. \tag{5}$$

Equation (5) 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 i vs the US, $\left[\mathbb{E}\left(X'_{i,c}\right) - \mathbb{E}\left(X'_{f,us}\right)\right]$. The second term, labeled 'Returns', captures differences in wages predicted by the estimated differences in returns across countries, $[\beta_i - \beta_{us}]$.

We implement this decomposition to the wage differential in each country in the sample 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 freelancer is "Top Rated"), iii) 91 detailed occupation-level dummies indicating whether the freelancer is listed in an occupations, and iv) 200 dummy

Figure 6: Endowments and price levels



Notes: The x-axis reports the (log of) the relative price level of output computed by the PWT (variable pl_gdpo). The y-axis reports relative wages computed predicted by the terms labeled 'Endowment' and t'Returns' in equation (5).

variables for each test that indicate if the freelancer has taken the test, along with 200 variables indicating the freelancer's score in each test.

Figure (6) reports the results of this decomposition. The left panel reports the decomposition across US states. The blue circles in the figure show the wage differentials predicted by the term labeled 'Endowment'. While there are some differences in worker characteristics across countries, these differences are not correlated with cross-country differences in price levels. In contrast, the red circles show the wage differentials predicted by the term labeled 'Returns'. Differences in returns are strongly correlated with aggregate price levels across countries.

The right panel shows the decomposition of the wage differentials across US states. Here, we see that differences in Endowments do play an important role in shaping for the cross-state wage differentials, accounting for about half of their variation. Differences in returns account for the remaining half. We summarize these results below:

Fact 2. *Cross-country differences in wages are almost exclusively driven by cross-country differences in returns. In contrast, about half of the differences in wages across US states are driven by differences in workers' characteristics.*

3.2 Wage differentials across occupations

We conclude this section by documenting occupational differences in cross-country wage differentials. In particular, within occupation o, we compute relative wages between each country and the US as:

$$rer^{w,o}_{i,us} = w^o_i - w^o_{us}, \tag{6}$$

where

$$w^o_i = \frac{1}{N^o_i} \sum_{f \in i} w^o_f, \tag{7}$$

is the average log-wage across all freelancers in country i that are listed in occupation o. We compute these relative wages for each of the 12 broad occupation listed in Appendix Table A1. We then compute, for each occupation, the slope of a regression between $rer^{w,o}_{i,us}$ and the relative price of output obtained from the PWT, analogous to the one presented in Figure 5.

The first column in Table 4 report the corresponding slopes with standard deviations in parentheses. There are substantial differences in wage differentials across occupations. The occupations in which wages are more equalized are Engineering, Web Design, and Translation services. Arguably, these occupations are characterized by producing tasks that can be easily traded across countries. In contrast, the largest wage differentials arise in Sales, Legal, and Accounting, which may require country-specific knowledge and impose barriers of entry to foreign workers. We note, however, that wages are not equalized even in the most easily traded occupations. The next two columns of the Table shows that wage differentials are mainly driven by differences in returns in most occupations. Endowments are relatively more important only in categories such as "legal" and "writing", where more country-specific skills may be required.

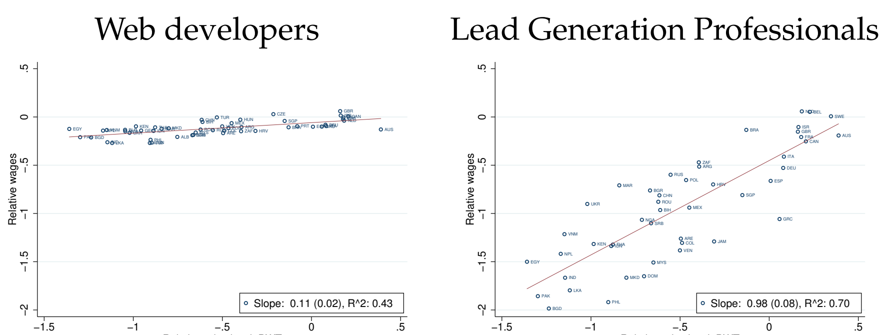
We further evaluate these differences by repeating this exercise for the 91 detailed occupations listed in the platform. Figure 7 illustrates that the differences in wage differentials among the most-and least tradable occupations can be quite dramatic. Table 5 reports occupations with the 5 highest and 5 lowest slopes. Wage differentials are as big as price differentials in 'Sales and Management' occupations, such as Data Mining Management, Lead Generation Professionals, Financial Planers, and Other Accounting and consulting specialist. In contrast, the smallest wage differentials are in Design occupations, such as Web Developers and Game Developers, Interior Designers and Architects. We note that, for the vast majority of occupations, the slopes of the regressions are well within zero and one, indicating that wages are far from being equalized, yet differences in wages are smaller than those in price levels. We summarize these observations below:

Table 4: Relative wages across occupations

Sector	Slope		Slope returns		Slope end.		Countries
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Sales	0.80	(0.07)	0.68	(0.05)	0.12	(0.04)	61
Legal	0.72	(0.13)	0.24	(0.31)	0.48	(0.36)	31
Accounting	0.66	(0.11)	0.61	(0.08)	0.05	(0.05)	56
Writing	0.54	(0.06)	0.39	(0.09)	0.15	(0.07)	61
Data	0.52	(0.11)	0.49	(0.11)	0.03	(0.06)	61
Admin	0.52	(0.05)	0.55	(0.05)	-0.03	(0.02)	61
IT	0.48	(0.07)	0.37	(0.07)	0.12	(0.06)	60
Design	0.46	(0.06)	0.42	(0.05)	0.04	(0.03)	61
Service	0.45	(0.07)	0.44	(0.08)	0.00	(0.06)	61
Engineering	0.41	(0.06)	0.38	(0.09)	0.04	(0.09)	59
Web	0.38	(0.06)	0.34	(0.04)	0.04	(0.03)	61
Translation	0.36	(0.05)	0.32	(0.09)	0.03	(0.1)	59

Notes: The table reports, for each broad occupation, the estimated coefficient and standard errors of regression of relative wages on the relative price of output.

Figure 7: Relative wages across occupations



Notes: The x-axis reports the (log of) the relative price level of output computed by the PWT (variable pl_gdpo). The y-axis reports relative wages computed according to equations (2) and (3) for Web Developers (left panel) and Lead Generation Professionals (right panel).

Table 5: Relative wages: Detailed occupations

Sector	Slope		Countries
Data Mining Management Freelancers	1.10	0.18	29
Lead Generation Professionals	0.98	0.08	46
Financial Planners & Advisors	0.95	0.14	25
Other - Accounting & Consulting Specialists	0.90	0.10	29
Market Researchers, Customer Researchers	0.83	0.08	49
ERP / CRM Implementation Specialists	0.33	0.10	27
Architects	0.31	0.09	27
Interior Designers	0.28	0.12	24
Game Developers	0.25	0.07	38
Web Developers	0.11	0.02	52

Notes: The table reports, for each broad occupation, the estimated coefficient and standard errors of regression of relative wages on the relative price of output.

Fact 3. *Cross-country differences in wages are pervasive across occupations, though are substantially smaller in more tradable occupations.*

4 Exchange rate pass-through

In this section, we evaluate how wages adjust to changes in the nominal exchange rate. In the previous section, we documented that relative averages wages in a country are strongly associated with relative prices. The degree of exchange rate pass-through to wages is informative about the wage setting process and the outside option of freelancers in this platform. For example, if this market is completely segmented and the outside option of the freelancer consists of a job in the local labor market, wages (which are quoted in US dollars in the platform) should respond to changes in the nominal exchange rate in order to track the expected wage in local currency. If instead this market was perfectly competitive, wages in this platform should not respond to changes in the exchange rate.

For this, we make use of the data on freelancers' job history, which provides information of the start date of a job and the hourly wage. The analysis is restricted to jobs that were billed on an hourly basis, where we can observe the actual hourly wage. Since not every freelancer works in any given month, we estimate the degree of exchange rate pass-through in the medium run.[3] More specifically, we estimate the following equation

$$\Delta w_{f,c,t} = \beta \Delta e_{c,t} + \Delta T + \varepsilon_{f,c,t}, \tag{8}$$

where $\Delta w_{f,c,t}$ is the change between the log-hourly wage that freelancer f from country c earned in a job that ended in period t and the wage earned in the immediately previous job, ΔT is the number of months that passed between those subsequent jobs (and captures the trend in wages), and $\Delta e_{c,t}$ is the cumulative change in the bilateral nominal exchange rate (measured as units of local currency per US $) during the time in between jobs. The coefficient of interest is β, which measures the responsiveness of wages (in US $) to changes in exchanges rates.

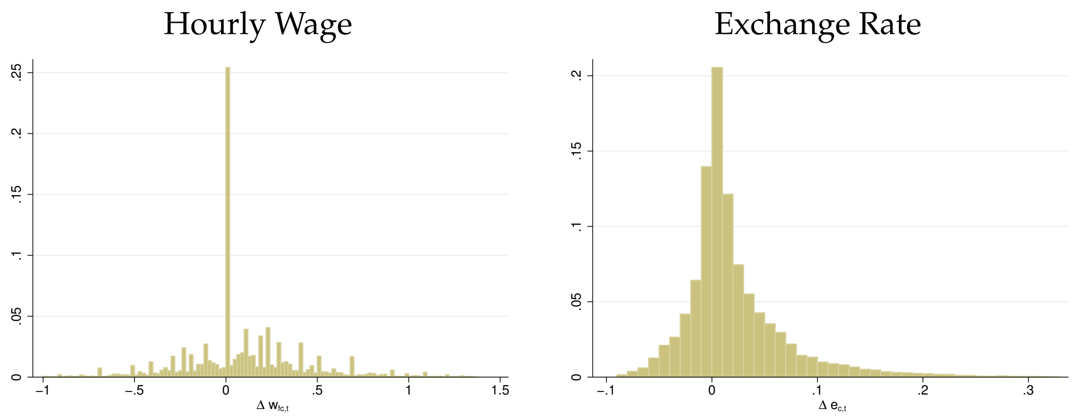
We begin the analysis by documenting how wages and exchange rates changed during the sample period. Figure 8 shows that there is substantial variation in terms of how freelancers' wages change in between jobs. However, it also shows that there is a large mass of zero wage changes. Table 6 presents summary statistics about the distribution of wage changes in between subsequent jobs. Overall, in around 25% of the cases freelances did not change their hourly wage. This number decreases to 19% for jobs separated by more than the median time gap. When focusing on job pairs with a gap of one month, we find that wage changes occurred in 70% of the cases. This shows that this market exhibits wages that are more flexible relative to other labor markets.[4] Conditional on a wage change, 64% of changes are increases and the median wage increase is 26%. Both statistics are increasing in the time gap between subsequent jobs. Conditional on a wage decrease, the median decrease is 22%. The second panel of Figure 8 shows that there is also large variation in terms of the behavior of exchange rates, with observations of both large depreciations and appreciations.

Table 7 reports the results of estimating equation (8). The pass-through of exchange rates to wages in USD is -0.107 and statistically different from zero. Therefore, if the Indian Rupee depreciates by 10%, the hourly wage in USD of an Indian freelancer decreases by 1.07%, which means that the hourly wage in Indian Rupees increases by 8.93%. Part of this low degree of pass-through could be due to nominal rigidities. To test this hypothesis, in the second column of Table 7 we estimate equation (8) conditional on a non-zero

[3] A similar approach has been followed in the literature on exchange rate pass-through into prices (see, e.g., Gopinath et al. (2010)).

[4] The degree of flexibility of wages in the platform is closer to that of job switchers, than those of job stayers (see Grigsby et al. (2019)).

Figure 8: Changes in Wages and Nominal Exchange Rates during the Sample Period



Notes: The figures report the distribution of hourly wage and exchange rate changes. The main text describes how changes in wages are computed.

Table 6: Frequency of 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	0.68	0.29	-0.22

wage change. The degree of pass-though increases to -0.123, which is quite similar to the baseline estimate. Thus, we conclude that nominal rigidities are not the main driver behind the low estimated pass-trough.

Next, we explore whether wages respond differentially to exchange rates depreciations than appreciations. Table 8 presents the estimation of a more flexible version of specification (8), which allows for differential pass-through to depreciations ($\Delta e_{c,t} \geq 0$) and appreciations ($\Delta e_{c,t} < 0$). The results show that wages are quite responsive to appreciations, with a pass-through of -0.44, but do no react to exchange rate depreciations. The difference becomes larger once we condition on non-zero wage changes: the responsiveness of wages to appreciations increases to -0.61. Thus, freelancers adjust wages in the platform when changes in the exchange rate decrease the wage expressed in local currency (i.e., when the exchange rate appreciates), but do not adjust them when changes in the exchange rate increase the wage expressed in local currency. Thus, wages in US $

Table 7: Exchange Rate Pass-through

	(1) $\Delta w_{f,t}$	(2) $\Delta w_{f,t}$
$\Delta e_{c,t}$	-0.107**	-0.123**
	(0.042)	(0.048)
[1em] ΔT	0.008***	0.008***
	(0.001)	(0.001)
N	105229	80059
Specification	-	$\Delta w_{f,t} \neq 0$

Notes: The table the results of estimating equation (8). The first column uses the full sample. The second column restricts the sample to non-zero wage changes.

Table 8: Asymmetric Exchange Rate Pass-through

	(1) $\Delta w_{f,t}$	(2) $\Delta w_{f,t}$
$\Delta e_{c,t} \times 1\{\Delta e_{c,t} \geq 0\}$	-0.064	-0.064
	(0.044)	(0.049)
[1em] $\Delta e_{c,t} \times 1\{\Delta e_{c,t} < 0\}$	-0.442***	-0.608***
	(0.109)	(0.135)
[1em] ΔT	0.008***	0.008***
	(0.001)	(0.001)
Observations	105229	80059
Specification	-	$\Delta w_{f,t} \neq 0$

Notes: The table reports pass-through coefficients for both positive and negative changes in the nominal exchange rate.

appear to be downward rigid.

5 Conclusion

This paper used a novel dataset on wages collected online to disentangle the sources of international wage differentials. We show large wage disparities across freelancers from different countries working on narrowly defined occupations. These wage differentials across countries are not driven by differences in observable worker characteristics. Real exchange rate levels account for about 50 percent of the cross-country-variation in average wages, and the elasticity of relative wages with respect to the real exchange rate is about 0.4. The magnitudes of these findings are pervasive across different country groups and types of jobs.

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Table A1: List of Occupations

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

Table A1: (cont.) List of Occupations

Detailed occupation	Broad Occ.	Detailed occupation	Broad Occ.
Contract Law Freelancers	Legal	Desktop Software Developers	Web & soft.
Corporate Law Professionals & Consultants	Legal	Ecommerce 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		