The Global Market for Remote White-Collar Jobs

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Abstract

We document several facts about cross-country remote work using data on 200,000 white-collar workers from 195 countries working for 20,000 firms. First, countries specialize in occupations according to their comparative advantages in cognitive and language skills. Second, cross-country wage disparities in international remote hiring are narrower than those observed in traditional domestic hiring. Third, by connecting workers and firms across borders, global remote work generates a median annual surplus of $52,480 per contract. Workers from wealthier countries capture a larger share of this surplus but experience smaller proportional gains.

JEL Codes: F23, F66, J31, J61

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1 Introduction

Economists estimate that nearly two fifths of the jobs in the United States can be done from home, the majority of which are in the service sector (Dingel and Neiman (2020)). If a job can be performed remotely, it can theoretically be done anywhere in the world (Freund and Weinhold (2002)). Remote work can break traditional barriers to hiring foreign workers, such as immigration restrictions. Digitally delivered service exports—which include cross-country remote hiring—doubled in the last decade, reaching $4 trillion worldwide in 2023.[1]

Compared to manufacturing trade, which has long defined globalization, the globalization of white-collar jobs presents unique opportunities and challenges (Baldwin (2022), World Bank and World Trade Organization (2023)). It often requires no physical movement of workers, capital, or products, making geographical distance less relevant. New types of trade frictions such as time differences can arise. Moreover, white-collar roles require different skills from manufacturing, often more cognitively demanding and communication-intensive, potentially reshuffling countries' statuses in global trade and giving rise to new forms of comparative advantages. Finally, the particular context we study, remote hiring of foreign workers, features direct integration of vastly different labor markets. It often happens within the boundary of an organization, with workers on different continents working together on the same team. New questions emerge regarding wage-setting for workers in comparable roles who reside in countries with substantial income disparities. These distinct features that differentiate white-collar globalization from traditional forms of globalization highlight the need for empirical evidence to inform policy discussions.

To provide evidence on the reality of white-collar globalization, we put together a unique dataset of cross-border remote work. We rely primarily on a dataset from Deel, a global human resources company. The dataset encompasses more than 20,000 firms globally, detailing their work relationships with over 200,000 foreign, remote, and predominantly white-collar workers (e.g., software engineers, product managers, and translators) across 195 countries. We complement our data on cross-border work relationships with up-to-date information on workers' and firms' domestic options, which we obtained from a widely-used salary aggregation website Glassdoor.

Enabled by our data, we answer three sets of research questions: (i) What factors influence countries' participation and occupational specialization in cross-border remote work?; (ii) What happens to cross-country wage inequality when labor markets are globalized and what is the role of firms in particular?; (iii) What are the gains for workers and firms as a result of cross-country remote hiring and how do the gains vary by country and occupation?

We start by looking at the location preferences of firms when remote work removes the constraints to hire domestically. We note three interesting patterns before delving into countries' com-

[1]Source: Digitally Delivered Services Trade Dataset, World Trade Organization

parative advantages. First, while wealthier countries demand and supply more remote foreign workers, the income gradient is much weaker on the labor supply side—workers from countries across the income spectrum engage in remote work for foreign firms. This finding aligns with patterns seen in foreign direct investment, which typically involves establishing physical entities abroad and is more relevant for manufacturing (see Antràs and Yeaple (2014) for a review). Second, workers from higher-income countries sort into different occupations compared to workers from lower-income countries. Relative to the overall distribution in the data, workers from high-income countries such as United States are over-represented in sales; workers from upper middle-income countries such as Argentina are over-represented in computer programming; and workers from lower middle-income such as the Philippines are over-represented in customer service. Third, using both the number and the total worth of contracts as outcomes in a standard gravity model, we find that geographical distance plays a smaller role in remote service trade than in traditional goods trade, whereas sharing a common language is significantly more influential. The effect of time zone differences is ambiguous, potentially reflecting both the demand for round-the-clock coverage and the need for synchronous collaboration.

Leveraging the diversity of occupations in our data, we examine the factors driving countries' occupational specialization in cross-border labor markets. We investigate whether certain characteristics of a country or country pair are particularly influential for occupations with certain skill requirements (Hanson and Liu (2023) implemented a similar approach in the context of immigration). We find that countries with stronger math training, measured by PISA scores, are more likely to specialize in more analytical occupations, such as statisticians and accountants. A one standard deviation increase in an occupation's analytical skill demands—approximately the difference between customer service agents and computer programmers—raises the elasticity of cross-country contracts with respect to PISA math scores by 134% in levels. Occupations with a higher emphasis on communication, such as editors and human resources specialists, have a greater preference for workers from countries with a shared language. The elasticity of contract number with regards to sharing a language is 22% higher in levels for a one standard deviation increase in an occupation's communication intensity. These results demonstrate that human capital factors, including math training and language proficiency, play an important role in determining the flows of white-collar globalization.

In the second part of the paper we focus on wages. We complement our data on wages paid in cross-country remote hiring with domestic wages obtained from Glassdoor. We find that despite workers and firms no longer being bound to their domestic labor markets, occupation-specific wage levels in both the worker's and the firm's country influence wages in cross-country hiring. We estimate an elasticity of 0.384 for cross-country wages with respect to occupation-specific wages in the worker's country. On the one hand, the fact that this estimate is much smaller than one suggests that access to foreign firms could go a long way in reducing cross-country wage inequality. On the other hand, the fact that it is greater than zero implies that workers in higher-income countries still earn more than workers in lower-income countries. We show that this positive elasticity holds within firms, within occupations, and within industries. Interestingly, when we adjust realized wages for purchasing power in the worker's country, the relationship with the worker country's occupation-specific wage turns from positive to negative. Although workers from higher-income countries receive higher nominal wages in the globalized labor market, they do not necessarily earn more in terms of purchasing power—if anything, they earn less. This shift suggests that cross-country remote work could benefit workers in regions with lower living costs by partially decoupling wages from local economic conditions.

We further unpack the cross-country inequality in nominal wages by considering the role of differential worker-firm matching. We show that differences in firm premia explain 50% of the remaining wage differences between workers in high-income and non-high-income countries. Furthermore, we show that around two-thirds of this 50% is due to the sorting of workers into firms (the "sorting channel"), while around one-third is due to differences in the wages of workers within firms (the "within-firm channel"). The existence of firm-wide wage-setting in labor markets across geography, which is behind the sorting channel, echoes the findings by Hjort et al. (2020) who show that wages in multinationals are anchored to wages at the headquarters. While we are not able to exactly identify what leads to these differences between workers in high-income and non-high-income countries, we suspect that the sorting channel is associated more with human capital differences across workers from different countries and various hiring frictions (e.g., uncertainty about worker ability), while the within-firm channel is more associated with the differential bargaining positions of workers in different countries. We leave investigation of these precise mechanisms to future research.

In the third and final part of the paper, we quantify the surplus generated by cross-border remote work. We focus on four key metrics: (i) the total surplus for participating firms and workers, calculated as the difference between each party's domestic alternative; (ii) the worker's share of this surplus, defined as the worker's surplus (wage minus domestic option) divided by the total surplus; (iii) the worker's gain, measured as the wage increase relative to their domestic alternative; and (iv) the firm's gain, measured as the wage savings compared to its domestic alternative. A caveat to our results is that they do not account for potential productivity differences between domestic workers and foreign remote workers. If foreign workers are less productive, our estimates of total surplus and firms' gains should be interpreted as upper bounds.

Assuming that workers and firms participating in cross-country remote hiring are representative of their respective country-occupation groups, we estimate the median realized total surplus to be 52,480 USD per contract per year. This surplus is approximately evenly split between workers and firms when accounting for purchasing power differences. Under alternative assumptions on the selection of workers and firms, we estimate workers' wage gains to range between 54–200% and firms' wage savings to range between 30–60%.

We conclude by examining how the surplus metrics vary by country and occupation. Our findings show that workers from wealthier countries and those in higher-skilled occupations receive a larger share of the surplus from cross-border remote work. Moreover, while workers in lower-income countries generally receive lower absolute wages in cross-country remote roles, they experience a higher proportional wage gain compared to workers in higher-income countries. Additionally, workers see a higher wage gain when employed by firms in richer countries or in more skilled occupations—factors associated with higher wages. It is worth emphasizing that these patterns are not mechanical but are driven by the specific wage structures observed in our data.

Relation to the literature While our paper is unique in the economic literature in providing empirical evidence on cross-country remote hiring of white-collar, full-time-like workers, other papers have explored related contexts. One line of related research is on online gig work platforms such as Freelancer and Upwork where firms and workers collaborate on short-term, often-remote tasks (examples include Agrawal et al. (2015) and Stanton and Thomas (2021)). The most closely related paper in this context is Brinatti et al. (2021) who show remote wages are higher for workers from countries with a higher per capita income. We replicate this fact in our context, which features longer-term jobs; and besides the worker country's per capita income, we also consider the influence of occupation-specific wages in a worker's home country, which better measures the worker's domestic alternative. While the average contract length in our data is over six months, the average task on Upwork takes around 75 hours, or ten working days, to complete (Stanton and Thomas (2021)). The type of work relationships we study, therefore, is longer-term and has the potential to provide a larger and more stable income stream for workers, as well as more pronounced benefits for firms.

Another line of related research focuses on foreign direct investments (see Antràs and Yeaple (2014) for a survey). The most closely related papers in this literature are Hjort et al. (2020) and Hjort et al. (2022), who study wages across establishments within the same firm (see also Drenik et al. (2023) and Minni (2024)). Our context is different in that the foreign workers we study predominantly work remotely and are not organized into physical establishments. This arrangement allows greater location flexibility, lower fixed costs for firms, and more seamless integration of foreign workers into the firm's organizational structure. Consequently, location preferences and wage patterns may differ from those observed when firms establish foreign subsidiaries.

Without remote work, workers have historically had to migrate to work for firms located in a different country. Our paper is therefore also related to the large literature on high-skilled migration (recent work includes Kerr et al. (2015), Kerr et al. (2016), and Amanzadeh et al. (2024); see Dustmann et al. (2016) for a survey). Also related is Muñoz (2023) on temporary migration for work in the European Union. Our paper highlights that the physical crossing of borders is not necessary for the globalization of labor markets, but some of the findings in migration still ring true, e.g. findings of comparative advantage in Hanson and Liu (2023).

Notably, most of our findings are not only novel within the context of cross-border remote hiring but remain under-explored in the globalization of services in general. These include insights on how countries' comparative advantages shape occupational specialization, the role of firms in cross-country wage gaps within globalized labor markets, and the size and split of the surplus from trade.

Structure of paper This paper proceeds as follows. We first further discuss the context and data in Section 2. We then discuss location preferences in cross-country hiring in Section 3; wage patterns in Section 4; and the role of firms in cross-country wage inequality in Section 5. We then estimate the size and distribution of surplus gained from cross-country hiring in Section 6. We conclude in Section 7.

2 Context and Data

2.1 Context

We use novel data from Deel, a human resources company that helps over 20,000 firms around the world hire, manage, and pay global teams. Deel was founded in 2019 and has grown rapidly in recent years. Through Deel, over $10 billion in remuneration has been paid to workers around the world.

Traditionally, temporary employment agencies and staffing firms have facilitated the hiring of foreign workers. These firms have workers on file whom they contract out to their clients. Deel differs from staffing agencies in that it does not help firms find workers. Rather, firms come to Deel with foreign workers whom they want to work with and Deel ensures compliance with local labor laws, including contracts, minimum wage, termination, and worker benefits. Deel also helps firms run payroll for foreign and domestic workers. If a firm wants to hire a worker in a country where the firm does not have a legal presence, Deel's local entity can serve as the employer of record. Before Deel's entry, there were a few companies that had a similar business model. In the last decade, a number of platforms have entered the market for international contractor and employer of record services, which has further surged amidst the rise of remote work during the COVID-19 pandemic.

Deel charges its clients a fixed monthly fee per worker, starting at $599 for its Employer of Record service, and $49 for contractors.[2] In contrast to firms like Upwork, work contracts on Deel are longer in length and pay more, as discussed in Section 2.3. Deel operates in over 150 countries, can serve as an employer of record for firms in more than 100 countries, and can pay workers in over 120 currencies. This wide international coverage provides us with a setting where the legal and logistical challenges of hiring across different countries are substantially reduced, a setting

[2]Note again that these fees are fixed, and thus do not vary by the worker's location, occupation, or wage.

that can reveal firms' underlying preferences for workers across the world. This business model facilitates the unique dataset that Deel has (and that we discuss in Section 2.2): a global matched data set of workers working remotely for firms.

2.2 Data description and sample restrictions

The data covers a sample of work relationships processed on Deel from 2021 through 2023. It has been filtered, anonymized, and aggregated in compliance with the European Union's General Data Protection Regulation (GDPR). For each work relationship, we observe the start and end dates, the pay rate and pay frequency, the overall pay, the currency used, the occupation, and the seniority of the worker.[3] Note that we only observe the end date if the contract is complete; in other words, we do not observe the intended end date of the contract. For in-progress contracts, we set an end date of September 2023, which is when we received the data.[4]

We also observe a dummy identifier for the firm as well as a dummy identifier for the worker. Importantly, the firm identifier allows us to match workers within a firm. For each firm, we have the firm's industry and location, while for each worker we have the worker's location. See Appendix B.1 for more information on the data we have, including how we construct the hourly wage and total earnings.

We make the following sample restrictions to the data. First, we limit the sample to work relationships that have positive income. This is to ensure that we only consider relationships for which work actually occurred. Second, we limit the data to firms that have one location used. This restriction is made so that we limit our analysis to firms that we can reliably verify their home location. These two sample restrictions successively reduce the sample size by 8.6% and 19.3%, respectively. Lastly, due to potential measurement errors in how the wages are constructed, we winsorize the top and bottom 10% of all wages.

2.3 Summary statistics

Table 1 provides summary statistics at the contract-, worker-, and firm-level. There are more than 200,000 contracts in total in our sample, where the median contract length is 5 months with an hourly wage rate of 16.52 USD.[5] Most contracts (92% and 63%) represent cross-country and cross-continent relationships, respectively. Note that only 21% of contracts have actually been

[3]The seniority of a worker is given by ten levels, spanning various amounts of experience.

[4]For very few cases, we see that the start date is after September 2023. For these cases, we replace the end date with one month after the start date. In the next subsection, we report the average length of contracts that started in 2022 or earlier, which are less influenced by the cutoff.

[5]Our data sample is a subsample of the contracts mediated by Deel. These statistics are based on the subsample only. We describe how we constructed the subsample in Section 2.2.

completed, with the rest ongoing. This suggests that the intended contract length might be longer than the median realized length of 5 months; indeed, contracts that started in 2022 or earlier, for example, have realized median contract lengths of 9 months.[6]

Table 1: Summary statistics

	Mean	SD	P25	P50	P75
Contract-level (N = 242,106)					
Contract length (realized, in months)	6.841	6.364	2	5	10
Start year	2022.346	0.689	2022	2022	2023
End year	2022.762	0.460	2023	2023	2023
Work contract completed	0.212	0.409	0	0	0
Same continent	0.368	0.482	0	0	1
Same country	0.082	0.274	0	0	0
Hourly wage (USD)	24.174	21.859	5.914	16.521	35.511
Worker-level (N = 207,044)					
Nb of work contracts	1.169	0.569	1	1	1
More than one work contract	0.125	0.331	0	0	0
Work length (months)	7.893	7.320	2	6	13
Work contract completed	0.248	0.550	0	0	0
Hourly wage (USD)	24.353	22.038	5.909	16.568	36.250
Nb of workers in firm	243.291	594.302	12	39	128
Worked for multiple firms	0.035	0.183	0	0	0
Firm-level (N = 22,629)					
Nb of workers	10.699	52.396	1	2	8
Nb of workers in same continent	3.922	24.784	0	1	2
Nb of workers in same country	0.870	7.050	0	0	0
Nb of unique worker countries	2.913	4.025	1	1	3

Table notes: Summary statistics shown at the contract-, worker-, and firm-levels. See Appendix B.1 for discussion of the wage variable.

There are more than 200,000 workers in total in the sample. Workers have 1.17 contracts on average; said otherwise, 12.5% of workers have more than one contract in the data. While most workers have only ever been hired by one firm through Deel, 3.5% of workers have worked for multiple firms. The median worker is in a firm that has 39 workers hired via Deel.

Lastly, there are over 20,000 firms in total in the sample. The mean firm hires 11 workers from 3 unique countries, while the median firm hires 2 workers from 1 unique country (which is also different from the firm's country). We emphasize that these are only workers the firms hired through Deel.

[6] In total, 54% of contracts started in 2022 or earlier. Further, of the 11% of contracts that started in 2021 or earlier, the realized median contract length is 11 months.

To conclude this subsection, we consider the location, occupation, and industry distributions of the work relationships. At the worker-level, workers are dispersed around the world: for instance, ten different countries each represent at least 3% of workers overall. On the other hand, hiring firms are primarily concentrated in the United States, Canada, and the United Kingdom, but include various other countries as well such as Sweden, Cyprus, the United Arab Emirates, Germany, and more. Finally, the most common occupations are software developers, customer support, and sales representatives, while the most common industries are computer software, information technology and services, and financial services.

2.4 External data

We enhance our proprietary data from Deel with three sets of external data.

First, we merge in data on occupations' skill requirements from Occupation Information Network (O*NET), a database of job characteristics sponsored by the U.S. Department of Labor. One question we ask in our paper is how a country's comparative advantages influence its occupational specialization based on the occupations' skill requirements in the global labor market. To measure occupations' skill requirements, we create a manual crosswalk between job titles in Deel's data (e.g. call center representatives) to O*NET occupations (e.g. customer support representatives). Although matching all tens of thousands of job titles in Deel's data to O*NET occupations is beyond the scope of the paper, we manually matched a subset of job titles that cover over 60% of the contracts in Deel's data.[7]

From O*NET data we create occupation-level measures of math and communication skills. We follow Deming (2017) and define the math skill of an occupation (which he also refers to as non-routine analytical skill) as the average of three survey questions related to math. To capture an occupation's communication requirement, we create a new variable by taking the occupational-level average of speaking ("talking to others to effectively convey information") and active listening ("listening to what other people are saying and asking questions as appropriate") skills. Communication skill and math skill have a correlation of 0.20 in the sample of occupations represented in the Deel data.

Second, we use external wage data at the country-occupation level. Finding standardized occupation-level wage data across countries can be challenging. One data source, the Occupational Wages around the World database (OWW; Freeman and Oostendorp (2002)) ends 10 years before the start of Deel's data and uses an occupation classification system from 1988 that does not provide sufficient coverage of service-sector jobs that can be done remotely.[8] We therefore use data

[7]For all job titles with at least 285 contracts in the Deel data, we manually matched each to an O*NET occupation, if there exists a corresponding occupation.

[8]OWW is sourced from ILO-run surveys to national governments. The occupation classification is based on the 1988 International Standard Industrial Classification (ISIC) and 1988 ISCO. Few of the occupations in the Deel data are part of the 1988 classification systems.

from another source, namely Glassdoor, an American website that collects self-reported company reviews and salaries from workers all over the world. We use Glassdoor's wage data to validate our wage data (in the next subsection), unpack wage determinants (in Section 4), and compute the surplus from cross-country hiring (in Section 6). The Glassdoor wage data is from 2019-2023. To ensure data quality, we use country-occupation pairs that have over 500 salary observations in that period. We also create a manual crosswalk between Glassdoor occupations (e.g. software engineers) and O*NET occupations (e.g. computer programmers).

Lastly, we use data on exchange rates, country characteristics, and country-pair shifters such as whether the two countries share a commonly spoken language and time differences from four sources. Exchange rates come from the OECD Exchange Rates database. We use the exchange rates to convert wages to USD. Country characteristics and bilateral shifters come from the 202211 version of the CEPII Gravity database (Conte et al. (2022)). We use these in gravity regressions in Section 3. In addition, we use the average math test scores among 15 year olds surveyed in 2022 by the OECD Programme for International Student Assessment (PISA) for a country's math training. Finally, we use the 2024 country classification from the World Bank that divides countries into four groups: high-income, upper middle-income, lower middle-income, and low-income.

2.5 Validation of wage data using an external source

To validate our data's quality, we take advantage of the subsample of thousands of domestic hires in Deel's data. The domestic subsample is dominated by contracts where the worker and the firm are both in the United States. Domestic wages are typically available for firms that choose to use Deel's human resources services for domestic hires in addition to their foreign hires. We find that firms for which domestic wages are available tend to have lower pay and have more workers (conditional on their mix of occupations and worker countries), both overall and foreign. Despite the potential selection issues, we believe it is still informative to check if the wages of the subsample approximate wages from an external source (namely, Glassdoor).

We do two exercises to compare wages of domestic hires in our data set with the self-reported domestic wages from Glassdoor. The Glassdoor data is at the country-occupation level while the Deel data is at the contract level. In the first exercise, we divide the hourly wage rates by the Glassdoor median rate for each domestic contract for which we can match a country-occupation salary from Glassdoor. If Deel's wages are distributed with the same median as the Glassdoor median, the median of the ratios should be one. We find that the median is 1.08, very close to 1, suggesting that Deel's data aligns well with wages reported on Glassdoor. In the second exercise, we regress the domestic wages on Deel on the median salary for workers in the same country and occupation as reported on Glassdoor. As shown in Figure 1, the coefficient is 0.69 and is significant at the 1% level. The fact that the coefficient is relatively close to 1 provides further assurance of the validity of Deel's data and our use of the Glassdoor data to proxy for outside options.

Figure 1: Domestic wages on Deel vs. domestic wages on Glassdoor

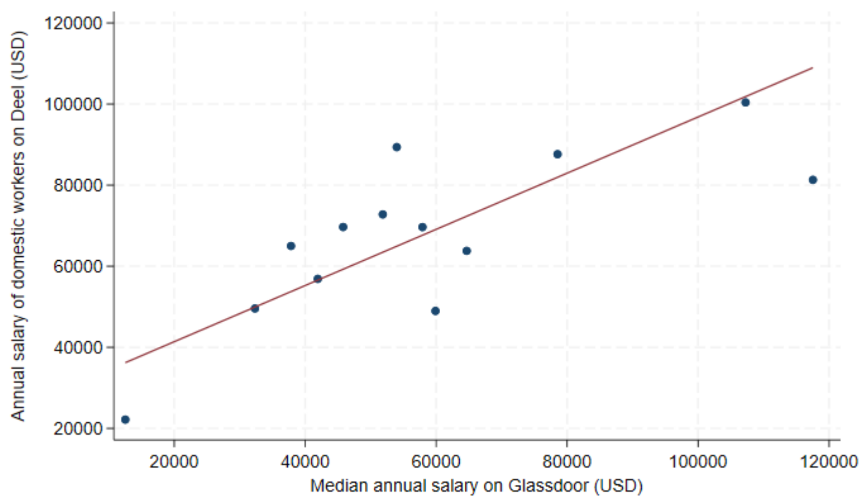

Figure notes: This figure is a binned scatterplot of Deel's wages against wages on Glassdoor in the same country and occupation. Each dot represents one or more country-occupation pairs. The slope is 0.69 (0.02).

3 Location Preferences in Cross-Country Hiring

In this section, we examine where firms hire from for remote white-collar jobs when they have the flexibility to hire from almost anywhere. We investigate the factors influencing these source location preferences and how these preferences vary across occupations. Our data is suitable for answering these questions because Deel enables firms to hire in any of the over 150 countries where it operates, minimizing the influence of legal and bureaucratic hurdles.

3.1 Notable patterns

We note some interesting patterns before moving on to a regression-based analysis on countries' comparative advantages.

Labor demand and supply by countries' income levels We begin by examining how the demand and supply of remote white-collar workers vary by country income level. In Figure 2, we plot the log number of cross-country contracts that firms in a country have, normalized by the country's population, against the log GDP per capita of that country. We do the same for the number of contracts that workers in a country have. The results indicate that wealthier countries exhibit a higher demand and supply for remote, cross-border white-collar workers, but the income gradient for worker supply is notably weaker. This weaker gradient in outward flows compared to that in inward flows mirrors findings by Antràs and Yeaple (2014) in the context of multinationals' foreign direct investments. They find that more developed countries have more outward and inward FDI flows than less developed countries, but the positive relationship is much more pronounced for outward flows. Unlike multinationals, however, the firms in our context do not necessarily own entities abroad while employing foreign workers remotely. Remote cross-border hiring therefore require lower fixed costs than FDI and are potentially more accessible to firms and workers alike. Despite the differences between our contexts, the similarity in the findings suggests that the factors driving firms to open offices abroad may also influence their decision to hire remote workers internationally. Likewise, the motivations leading workers to join multinational firms may similarly encourage remote work for foreign firms.

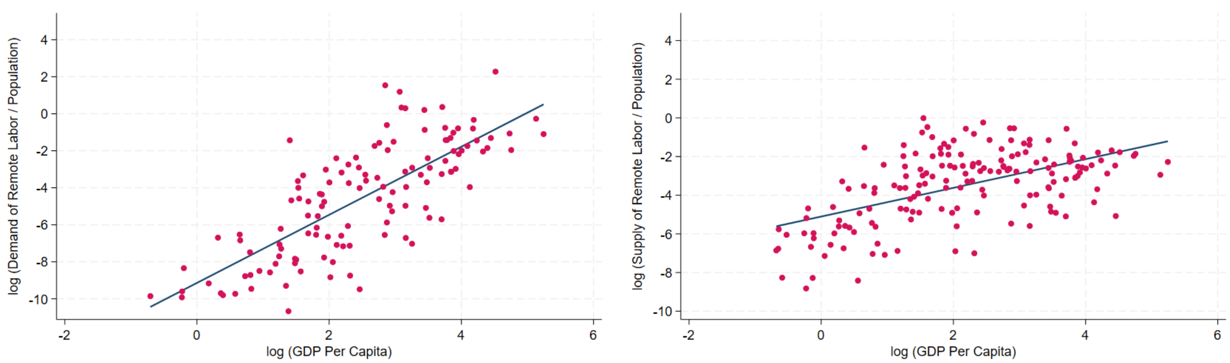

Figure 2: Labor demand/supply and countries' income

Figure notes: Demand (supply) is defined as the number of cross-country contracts that firms (workers) in a country have in our data. The slopes are 1.83 (0.14) and 0.74 (0.08), respectively.

Example occupations Although workers in countries of all income levels participate in cross-border remote work, they sort into different occupations. We conduct a more systematic analysis of countries' comparative advantages in cross-border remote work in Section 3.2. Here, we focus on the distributions of workers by their countries' income levels in the three most common occupations in our data: computer programmers, customer service agents, and sales representatives. For computer programmers, workers in upper middle-income countries claim half of the contracts while the two other country groups split the rest. For customer support agents, workers from lower middle-income countries almost match workers from upper middle-income countries, while for sales, high-income countries are the most popular source of workers.

Figure 3: Distribution of worker countries in the three most popular occupations

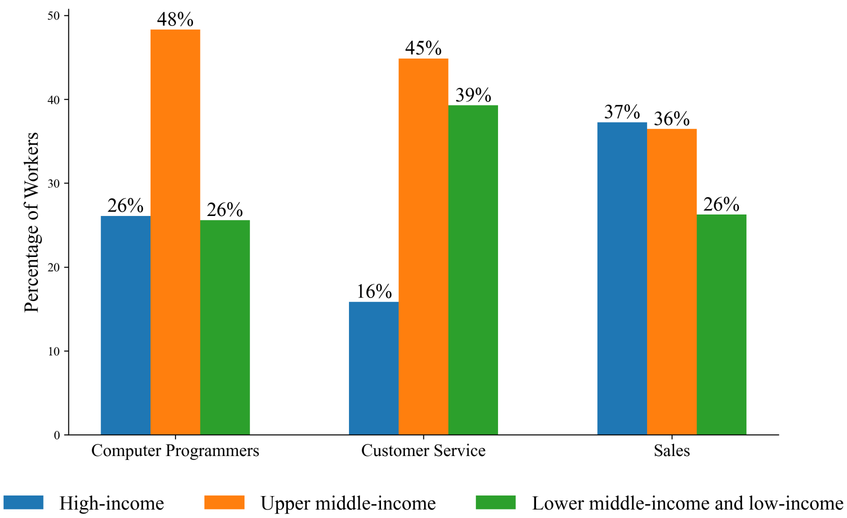

Figure notes: The sample is limited to cross-country contracts. The percentages are based on the number of contracts for workers in the respective categories of countries. Countries are grouped according to World Bank classification for the 2024 fiscal year.

Gravity estimates To further study the determinants of the location choices in cross-country hiring, we follow the international trade literature and estimate a gravity equation (early examples include Tinbergen (1962) and Anderson (1979)):

$$\ln T_{ij} = \ln\alpha_0 + \alpha_1 \ln X_i + \alpha_2 \ln X_j + \alpha_3 \ln D_{ij} + \ln\eta_{ij} \tag{1}$$

where T_{ij} is cross-country hiring of workers in country i by firms in country j, X_i (X_j) is a vector of country i's (j's) characteristics, D_{ij} is a vector of bilateral characteristics such as distance and time difference, and η_{ij} is the error term. We aggregate our data at the firm-worker level to construct two outcomes of cross-country hiring: the number of hires and the total compensation. The first outcome, the number of hires, is our preferred outcome because it is a more direct measure of firms' location preferences. The total remuneration, which is the product of the number of hires and the average payment, is confounded by pay differences among workers in different countries (which we will turn to in the following sections).

To form the sample, we include in i all the countries with at least one worker who participates in cross-country hiring in our data and in j all the countries with at least one firm that participates in cross-country hiring. Following Silva and Tenreyro (2006), our preferred estimator is the Poisson pseudo maximum likelihood (PPML) estimator on the full sample of country pairs, including country pairs for which we observe zero cross-country hiring. When applying the PPML estimator to the total remuneration, we winsorize the top 5% of the sample to limit the effect of measurement errors of remuneration. The results are in Appendix Tables A1 and A2. While column 3 is our preferred estimator, the main qualitative conclusions are the same across estimators.

We note three findings from the gravity regressions. First, the elasticities of the number of cross-country contracts and the total remuneration with regards to distance are -0.132 (0.216) and -0.112 (0.027), respectively. Our estimates show that distance has a much smaller influence on cross-border remote service trade than in traditional good trade. Silva and Tenreyro (2006) estimate that the elasticity of cross-country goods trade volume with regards to distance to be -0.784 (0.055). In goods trade, distance matters to a large extent due to the need to physically transport the goods (Anderson (1979)). Remote work eliminates the need of physical movement and is therefore less sensitive to distance. Second, we find a weakly negative relationship between cross-country remote hiring and time differences, defined as the absolute differences in hours between the capitals of the two countries. The elasticities of the number of cross-country contracts and the total remuneration with regards to time differences are -0.058 (0.075) and -0.078 (0.008), respectively. Our estimates likely reflect diverging incentives in cross-country hiring: some firms may want to hire workers with a large time difference to take advantage of the 24-hour work day while other firms may want to hire workers with a small time difference so that they can more easily collaborate with domestic workers. We show in Section 3.2 that the preferences for time differences depend on the occupation's analytical skills. Lastly, sharing a common language—such as Spain and Argentina—is associated with more hiring. Sharing a common language increases the number of hires by 156%. The emphasis on languages is consistent with the white-collar nature of the jobs that we study as these jobs potentially require significant verbal communication among international colleagues and with clients. In Section 3.2, we show that sharing a common language is more important for occupations that require a higher level of communication skills.

3.2 Comparative advantages

In this section, we study the factors that shape a country's occupational specialization in a globalized labor market. For example, we investigate whether countries with better mathematical training tend to specialize in occupations with higher demand for analytical skills, such as computer programming.

To explore these questions, we analyze how certain characteristics of a country — or country pair — predicts specialization in occupations along certain skill dimensions. Our approach is inspired by Hanson and Liu (2023), who run a similar analysis for immigrants to the U.S. and Canada.

Formally, we estimate the below regression at the occupation×worker country×firm country level:

$$\ln T_{ijo} = \ln(\text{Dist}_{ij}) + \ln(\text{Dist}_{ij}) \times \text{Analy}_o + \ln(\text{Dist}_{ij}) \times \text{Comm}_o + \ln(\text{Time}_{ij}) + \ln(\text{Time}_{ij}) \times \text{Analy}_o$$
$$+ \ln(\text{Time}_{ij}) \times \text{Comm}_o + \ln(\text{Lang}_{ij}) + \ln(\text{Lang}_{ij}) \times \text{Analy}_o + \ln(\text{Lang}_{ij}) \times \text{Comm}_o$$
$$+ \ln(\text{Math}_i) \times \text{Analy}_o + \ln(\text{Math}_i) \times \text{Comm}_o + \delta_i + \delta_j + \delta_o + \ln\eta_{ijo}, \tag{2}$$

where T_{ijo} is the cross-country hiring (in number of contracts) of workers in country i by firms in country j in occupation o. The skill requirements Analy_o and Comm_o, which come from O*NET, are normalized to have standard error 1 and minimum 0. For Dist_{ij} we use the log of geographical distance between two countries according to CEPII. For Time_{ij} we use the absolute hours of time difference between two countries' capitals. For Math_i we use log of countries' average math test scores in PISA 2022. For Lang_{ij} we use indicators for whether two countries share a primary or secondary language according to CEPII. We control for worker's country, firm's country and occupation fixed effects.

Table 2: Comparative Advantages of Countries by Occupation

	Baseline	$\times\text{Analytical}_o$	$\times\text{Communication}_o$
Distance_{ij} (log)	-0.735***	0.162**	-0.032
	(0.216)	(0.068)	(0.065)
$\lvert\text{Time difference}\rvert_{ij}$	0.121*	-0.062**	0.002
	(0.067)	(0.027)	(0.022)
Math_i (log)		1.335***	-0.646
		(0.497)	(0.549)
$\text{Common Language}_{ij}$	0.576**	-0.199*	0.223***
	(0.268)	(0.103)	(0.075)

Table notes: Coefficients for equation 2 are displayed. Worker's country, firm's country, and occupation fixed effects are controlled for and omitted from the table. Errors are clustered at the worker country × occupation and firm country × occupation levels. Standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

We estimate equation 2 using the PPML algorithm to accommodate the existence of small values in the outcome variables. We report the coefficients in Table 2. Column 1 displays the correlation between the number of contracts and the worker's country's or country pair's characteristics for an occupation with the lowest analytical and communication skill requirements. Columns 2 and 3 display the interactions between these characteristics and occupations' analytical and communication skill requirements, respectively.

We find that analytical occupations show a stronger preference for workers from countries with better math training. A one standard deviation increase in an occupation's analytical skill demands

— approximately the difference between roles like customer service and computer programming — raises the elasticity of cross-country contracts with respect to PISA math scores by 134% in levels. Moreover, more analytical occupations show a stronger aversion to hiring across large time differences, although the aversion is only significant at the 5% level and not at the 1% level. The aversion to time differences likely reflects a need for prompt communication across global teams in these analytical roles. We also find that more analytical occupations exhibit a weaker aversion to hiring workers from distant locations, though this effect is also significant at the 5% level rather than the 1% level. Finally, countries that share a language enjoy a substantial advantage in communication-intensive occupations. Specifically, a shared language increases hiring by 22% more in levels (39% change from baseline) for a one standard deviation increase in an occupation's communication intensity — roughly the difference between roles like computer programming and sales.

4 Wage-Setting Across Firms, Occupations, and Space

Now that we have shown where firms hire from, we consider how wages are set in this global context. We begin by estimating simple wage equations to understand what predicts wages. We then conduct a formal variance decomposition to determine how much variation different observable characteristics can explain in wages. We then conclude by estimating to what degree firms use global wage-setting when setting wages across space.

In the following wage analyses, we focus on fixed term contracts, because the wage data is most reliable for these workers. Fixed term contract workers make up a majority of the sample (they make up 55% of the overall sample). When applicable, we discuss how results compare for other types of workers as well.

4.1 Wage equation regressions

In this subsection, we estimate various wage equations, in order to determine what factors determine wages, and how this varies by occupation, industry, and space. In particular, we estimate the following equation:

$$\ln w_{ijoc} = \gamma_1 \ln(\text{domestic wage}_{io}) + \gamma_2 \ln(\text{domestic wage}_{jo}) + \gamma_3 X_{ijoc} + \epsilon_{ijoc} \quad (3)$$

where w_{ijoc} is the wage received by a worker in country i working for a firm in country j in occupation o in contract c, domestic wage$_{io}$ is the occupation-specific median wage in worker's country, domestic wage$_{jo}$ is the occupation-specific median wage in the firm's country, and X_{ijoc} are various controls (worker seniority, start month and year of contract, and contract pay frequency).

We then progressively add various fixed effects in order to estimate how the relationship between worker and firm country wages and realized wages depends on different economic factors (e.g., firm, occupation, industry, and country). To begin, we see in column (1) of Table 3 that the occupation-specific wage in the worker's country is positively associated with the wage workers actually receive. In particular, the elasticity is equal to 0.384. In Figure 4 and Appendix Table A3, we estimate the same equation as 3, but instead use the GDP per capita of the worker's country and firm's country, in order to directly compare our estimates to the related literature. When doing so, we find an elasticity of 0.266. Brinatti et al. (2021) report an elasticity of 0.23 based on wages from a sample of workers on a prominent online gig work platform, and Hjort et al. (2022) find an elasticity of 0.16 for workers in multinational firms' global offices. Our higher elasticity may be attributable to the fact that, unlike Brinatti et al. (2021), our sample reflects more conventional, full-time employment, and unlike Hjort et al. (2022), our workers across countries are more substitutable due to the predominantly remote nature of their roles. We argue that using occupation-specific wages—instead of GDP per capita—represents a substantial improvement, as it better reflects the relevant outside options for both workers and firms.

Table 3: Elasticity of wage to local labor market conditions

	Hourly wage (log)				
	(1)	(2)	(3)	(4)	(5)
Median occupation-specific wage in worker country (log)	0.384***	0.194***	0.414***	0.364***	0.373***
	(0.005)	(0.005)	(0.015)	(0.005)	(0.005)
Median occupation-specific wage in firm country (log)	0.338***	0.360***	0.280***	0.208***	0.321***
	(0.008)	(0.011)	(0.009)	(0.010)	(0.008)
Observations	33,231	30,515	33,231	33,231	30,846
Adjusted R-squared	0.391	0.755	0.436	0.410	0.417
Controls	Y	Y	Y	Y	Y
Firm FE		Y			
Worker country FE			Y		
Occupation FE				Y	
Industry FE					Y

Table notes: Sample is limited to fixed contract workers, and data for which we have Glassdoor wage data. Controls include worker seniority, start month and year of contract, and contract pay frequency. Standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

We next consider how this elasticity changes when we add various fixed effects. In Column (2), we add firm fixed effects to this regression, which decreases the elasticity by one half to 0.194. This suggests that part of why workers from higher-paying local labor markets earn more is because they are able to work for higher-paying firms. This is consistent with Hjort et al. (2022), who also find that the wage elasticity attenuates when including a firm fixed effect.

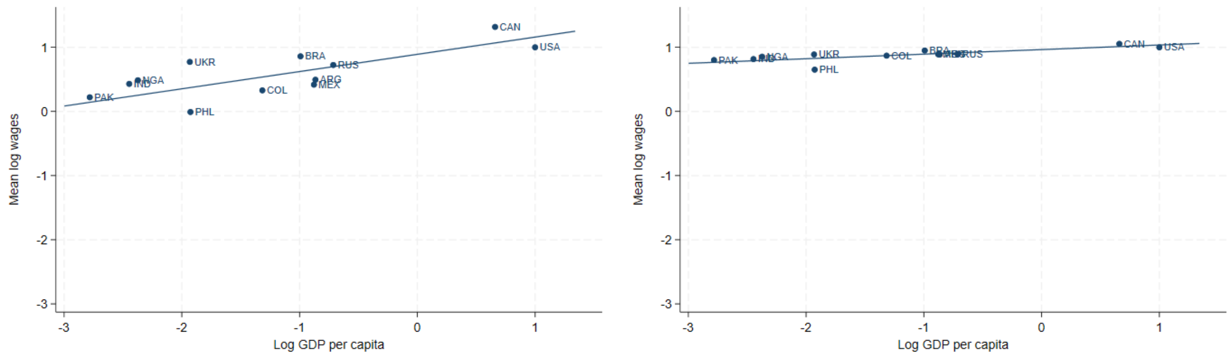

Figure 4: Cross-country wages and worker country's per capita GDP

Figure notes: The figure on the left controls for worker seniority, start month and year of contract, and contract pay frequency. The figure on the right controls in addition for firm fixed effects. Only countries with a large number of contracts are displayed in scatter plot. The slopes are 0.29 (0.04) and 0.05 (0.01), respectively.

One notable aspect of the context we study is that workers employed remotely by foreign firms generally remain in their home countries. Consequently, it may be sensible to adjust the wages of workers from different countries according to purchasing power parity (PPP).[9] When adjusting for local price levels, the coefficient on a worker's country's per capita GDP turns negative across all specifications (see Appendix Table A4). This implies that, among workers on fixed-term contracts, observably similar workers in lower-income countries earn less in nominal wages than their counterparts in higher-income countries but more in terms of local purchase power. This suggests that global remote work presents an especially important opportunity for workers in more disadvantaged areas by partially disconnecting wages from local economic conditions.

We also consider how the local labor market conditions of the firm—given by the median occupation-specific wage of the firm's country—affect the wages they offer. We find that the elasticity between the local labor market conditions of the firm and the realized wages is 0.338. This suggests that both the local labor market conditions of the worker and the local labor market conditions of the firm are important for wage determination. Nevertheless, when including occupation fixed effects, the elasticity with respect to the firm country decreases to 0.208, suggesting that firms in higher-paying local labor markets are hiring workers in higher-paying occupations. Our estimate is larger than the estimate in Brinatti et al. (2021) (0.06), but smaller than the estimate in Hjort et al. (2020) (0.531).

In Appendix Tables A5, A6, and A7, we estimate equation 3 for all workers, without limiting it to fixed contract workers. We find that while the overall elasticity is generally larger, other

[9]We use PPP levels from 2019 to adjust wages, avoiding potential distortions in prices due to the Covid-19 pandemic.

qualitative conclusions remain the same. In particular, we still see that the sorting of workers into firms explains a significant share of the wage elasticity.

We conclude this subsection by considering in Appendix Table A8 how the worker country-wage elasticity varies by the skill level of the occupation. To gauge skill level, we use the median wage for U.S. workers in that occupation, as reported by Glassdoor. Given that computer programmers earn the highest median wages in the U.S. (among the occupations in our sample) and represent the majority of contracts in our sample, we categorize occupations into "computer programmers" and "lower-skilled occupations," the latter including roles such as secretaries and sales representatives. We find that the elasticity of wages with regards to the wage in the worker's occupation-country is lower for computer programmers than for lower-skilled occupations (0.308 vs. 0.447), suggesting there is less pass-through of local conditions to wages in higher-skilled occupations compared to lower-skilled occupations. This is consistent with Hjort et al. (2022), who also find that the elasticity of wages with respect to local labor market conditions is lowest for the highest-skilled occupations. We contribute to the finding in Hjort et al. (2022) by showing that the relationship between the skill requirement of an occupation and the pass-through of local labor market conditions remains true when the work is conducted remotely.

4.2 Wage variance decomposition

4.2.1 Motivating summary statistics

We then further consider what drives wage variation in the data by conducting a formal wage decomposition. In particular, we now consider to what extent wages are explained by different observable characteristics. In all specifications, we control for the contract type, contract start year and month, seniority level, and pay frequency. As shown in Appendix Table A9, the standard deviation of the overall wage distribution is 21.64.

We then consider how the standard deviation in wages decreases after progressively controlling for various observable characteristics. After taking the residual with respect to the country of the firm, the standard deviation decreases by 3% to 21.11. Variation in wages across firms in different countries is almost as large as variation in wages across firms in the same country. This result could be driven by the fact that more than half of the firms in our data sample are located in the U.S., with the rest mostly in high-income countries as well. The largest decrease is when taking the residual with respect to the actual firm: the standard deviation decreases by another 33% to 13.88. The fact that wage variation is much higher across firms than within firms implies some degree of firm-wide wage-setting, which we turn to in Section 4.3. Taking the residual with respect to the occupation of the worker reduces it to 13.59, while further conditioning on the worker's country reduces this to 12.38. One might expect that the worker's country would explain a large share of the remaining wage variation if worker productivity varied by country and wages were reflective of productivity.[10] However, this is mostly not the case: within the same firm-occupation pair, the worker's country only explains 6% of the remaining variation. Thus, both (a) wages for workers in the same occupation in the same firm but from different countries are relatively similar and (b) workers in the same occupation in the same firm from the same country can still have different wages, despite the moderate level of wage compression that results from global wage-setting. Finally, the observable characteristics together, not including the worker ID, explain 43% of the overall standard deviation.

Including the worker ID allows us to explain another 29% of wage variation. Note that only 3.5% of workers have worked for multiple firms through Deel, and so this decreases the sample dramatically. When we conduct the same exercise on the sample for which we have these switchers, as in columns (3) and (4), we see the same qualitative patterns in terms of to what degree each observable can explain wage variation.

4.2.2 Formal decomposition

Motivated by these summary statistics, we now conduct a standard wage variance decomposition, akin to wage decompositions done commonly in the labor economics literature. We start with the following wage model

$$\ln w_{it} = \theta_{it} + \delta_{f(i,t)} + \beta X_{it} + \epsilon_{it} \tag{4}$$

where w_{it} is the wage of worker i in period t. θ_{it} are person characteristics (such as country), $\delta_{f(i,t)}$ are firm fixed effects, and X_{it} are other covariates (including occupation), all for individuals i in time t. Moreover, we include the same controls as in subsection 4.2.1. We progressively consider three models in Table 4, as we now discuss and as motivated by the preceding summary statistics.

In the first model, we just consider the worker's country and the firm's country. When doing so, the worker's country explains 27.9% of wage variation. Interestingly, the covariance between the worker country fixed effect and firm country fixed effect explains nearly zero of the variance (0.3). This suggests that firms located in higher-paying countries do not necessarily hire workers located in higher-paying countries. Firm country explains little of the wage variation because most of the firms come from only three countries, all of which are high-income.

In the second model, we replace firm country with the actual firm. Now, the explanatory power of the worker's country decreases. The worker's country only explains 11.9% of wage variation, while the firm itself explains 33.4%. Moreover, the covariance between the firm and the worker's

[10] One might expect this to be true given differences in human capital across countries. For instance, see Hendricks and Schoellman (2023) and Martellini et al. (2024), among many others, for analyses of how human capital and productivity varies across countries.

Table 4: Wage variance decomposition

	Variance explained (%)		
	(1)	(2)	(3)
Variance terms:			
Worker country	27.9	11.9	12.0
Firm country	1.1		
Firm		33.4	29.4
Occupation			2.9
Covariance terms:			
Worker country-firm country	0.3		
Worker country-firm		7.0	6.4
Worker country-occupation			0.5
Firm-occupation			1.7
Other:			
Residual	51.6	27.1	25.6
Number of observations	193,257	185,513	185,509

Table notes: This table shows the amount of wage variation explained by each regressor in three different wage equation specifications, as discussed in the text.

country explains 7.0% of wage variation. This means that higher-paying firms are indeed hiring more from richer countries.

Lastly, in the third and our preferred model, we include the worker's occupation. When we do so, the firm still explains a large amount of wage variation: 29.4%. Occupation explains 2.9%, while the covariance between the occupation and the firm explains 1.7%. Finally, the residual explains 25.6% of wage variation in the third model. While this share is larger than how much residual variation there typically is in matched worker-firm data sets with specifications including worker fixed effects, it is not too far off.[11]

We draw two main conclusions from the decomposition results. First, the worker's country still plays a big role in explaining wage variation in the cross-country hiring context. Second, the worker's country could matter mostly through their influence on which firms—conditional on a firm's country—the workers are able to work in. In the next section, we make this point more formally as we investigate the role of firm pay premium in cross-country wage differences.

Finally, we consider how the estimated firm fixed effects vary across worker countries, motivated by the fact that the covariance between the worker country and the firm explains a large amount of wage variation (6.4% in the preferred model). In Figure 5, we plot the average firm fixed effect by worker country and order it by the GDP per capita of the worker country. We see that workers from richer countries do indeed sort into firms that pay more on average. We more rigorously

[11] For example, the residual explains around 4-5% in Card et al. (2016), 5% in Card et al. (2018), 13% in Card et al. (2023), 12-14% in Card et al. (2013).

investigate sorting into firms in Section 5.

Figure 5: Firm fixed effect by worker country

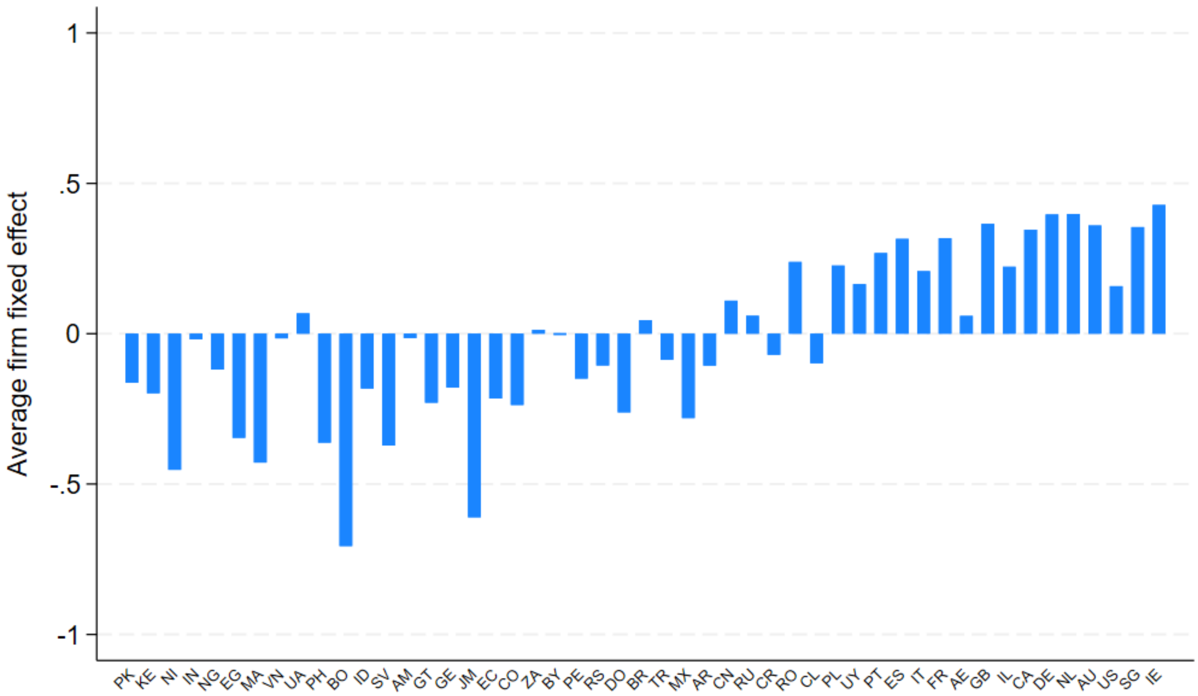

Figure notes: This figure plots the average firm fixed effect estimated in Equation 4 for each worker country. The figure is then ordered by the GPD per capita of the worker country.

4.3 The degree of global wage-setting

Now that we have shown the importance of firms in wage-setting in this international context, we now consider how wages vary within firms across space. The question of whether wages should be set uniformly within a firm (and thus set globally), or anchored to the cost of living for where the worker is located (and thus set locally) has been studied recently in a national context (e.g., Hazell et al. (2022) in the United States). However, this question has taken on new importance in the international context, where the cost of living varies even more than in any single country (e.g., Bloom (2023)). With that being said, research in the international context has focused on in-person work (e.g., Hjort et al. (2020)); we are the first to consider it for remote work.

We therefore ask: to what degree are wages for the same job equal across space within firms? We follow Hazell et al. (2022) in order to quantify the amount of global wage-setting. In particular, we calculate the difference in wages for within-firm job pairs. We define this as jobs that begin in the same year in the same occupation for the same firm, but in different countries. For example, we compare the wage for a software engineer within a given firm from Argentina with the wage for a software engineer in the same firm from Colombia, for workers that start at the same time. We then compare this to a benchmark where we ignore the firm, and simply compare workers in similar jobs across countries.

As seen in Figure 6, there is large variation for how wages differ for the same job within the same firm, but in different countries. First, the distribution of pairwise differences in wages is compressed when comparing jobs within the same firm, as compared to jobs across different firms. Second, 12% of job pairs offer roughly the same wage, while the median pairwise difference in wages is 28%. This suggests that there is some degree of global wage-setting, but that it is relatively limited in scope, especially compared to the amount of national wage-setting found in Hazell et al. (2022); they analogously find that 35% of jobs offer the same wage, with a median wage difference of 5%. To summarize, we find that while firms explain a large share of wage variation in the globalized labor markets, the evidence of firm-wide wage setting—setting the same exact wages for workers in different locations—is weaker in the global context compared to what researchers have found in a national context.

Figure 6: Within-job, across-country wage differences between and across firms

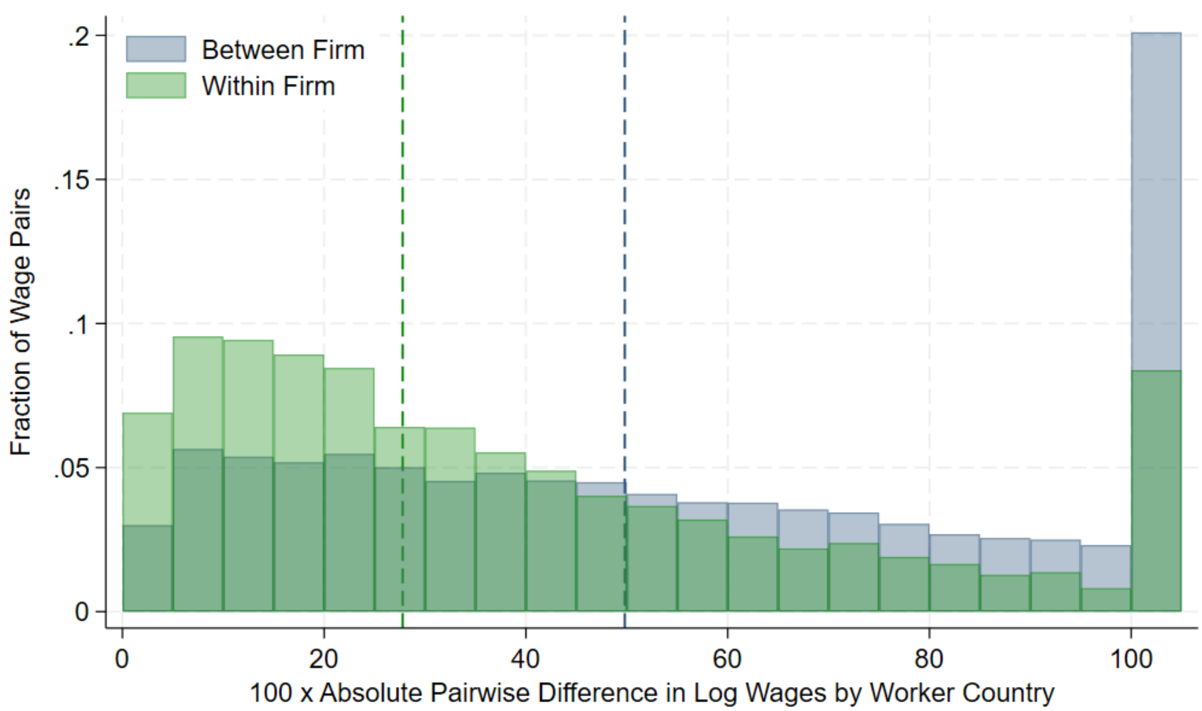

Figure notes: In the blue, we plot the distribution of wage differences for all pairwise jobs between firms. In the green, we plot the same, but for all pairwise jobs within firms. See the text for more detail.

5 The Role of Firms in Cross-Country Wage Inequality

Thus far, we have shown that global remote work leads to a compressed wage distribution across workers from different countries. We have shown descriptively in Section 4.1 that part of the remaining wage differences are due to differential sorting into firms. Furthermore, we showed in Section 4.3 that substantial pay differences remain when comparing workers in the same job—from different countries—within a firm. We now directly measure (a) the degree to which differences in firm pay explain differences in wages across countries and (b) how much of this is due to differential sorting into firms compared to within-firm pay differences. To do this, we conduct a decomposition exercise akin to the decomposition of the gender wage gap and the role of firms in Card et al. (2016).

We consider the role of firms in global hiring and wage-setting due to the wide variation in firm productivity, and the ability of firms to provide access to jobs to workers around the world, regardless of location. We view the sorting of workers from different backgrounds across firms as indicative of human capital differences across workers, potential hiring discrimination, and various hiring frictions (e.g., uncertainty about worker ability). We view pay differences within firms as indicative of how firms set wages across space and whether (and to what extent) they engage in global wage-setting, as discussed in Section 4.3.[12] While we are currently unable to provide direct evidence related to these hypotheses, we view this approach as a way to structure the analysis as well as motivate future research.

We closely follow Card et al. (2016) in our analysis of the role of firms in cross-country wage inequality. We aim to quantify the amount of cross-country wage inequality that is explained by firm pay premium. Moreover, we aim to divide the role of firm pay premium into the *sorting channel*—how workers sort across firms with different pay premium—and the *within-firm channel*—how different workers receive different wages within firms.[13] We note that because we do not observe a large number of workers switching firms, we cannot control for potential productivity differences among workers in different countries by estimating individual fixed effects as in Card et al. (2013).

5.1 Empirical specification

We begin by considering the wage gap between workers from two sets of countries, countries $\mathcal{J}$ and countries $\mathcal{K}$. In our main analysis, we consider the wage gap between workers from high-income countries (which we denote by country set $\mathcal{J}$) and workers from non-high-income countries (which we denote by country set $\mathcal{K}$), following the World Bank income classifications, as described in

[12] See Card et al. (2016) for a parallel discussion on why the firm is relevant when thinking about the gender wage gap.

[13] Card et al. (2016) refers to the latter channel here as the bargaining channel. We choose to refer to it as the within-firm channel, because in our context it could refer to various mechanisms in addition to bargaining.

Section 2.4.[14]

We then estimate the following model:

$$\ln w_{it} = \delta^{C(i)}_{f(i,t)} + \beta^{C(i)} X_{it} + \epsilon_{it} \tag{5}$$

where $C(i)$ is the country set for which worker i belongs, and can be either $\mathcal{J}$ or $\mathcal{K}$. Note that this model is similar to the model from Section 4.2.2 above, except that we allow for country set-specific firm fixed effects $\delta^{C(i)}_{f(i,t)}$ and country set-specific returns to the covariates X_{it} (we control for occupation, contract type, contract start year and month, seniority level, and pay frequency). Moreover, following Card et al. (2016), we restrict the sample to firms that hire at least one worker from each of country set $\mathcal{J}$ and country set $\mathcal{K}$, so that we are able to measure what firms would pay workers in each country set. We denote a particular country set such that $C(i) \in \mathcal{J}$ or $C(i) \in \mathcal{K}$ and we estimate this model for workers from the two country sets separately as discussed above. This specification then allows us to determine the contribution of firms to the wage gap between workers from high-income countries and workers from non-high-income countries.

We then decompose the overall contribution of firm pay premium towards the wage gap into a *within-firm channel* and a *sorting channel*, following closely Card et al. (2016):

$$\begin{aligned} E[\delta^{\mathcal{J}}_{f(i,t)} | \text{country set } \mathcal{J}] - E[\delta^{\mathcal{K}}_{f(i,t)} | \text{country set } \mathcal{K}] = {} & E[\delta^{\mathcal{J}}_{f(i,t)} - \delta^{\mathcal{K}}_{f(i,t)} | \text{country set } \mathcal{J}] \\ & + E[\delta^{\mathcal{K}}_{f(i,t)} | \text{country set } \mathcal{J}] - E[\delta^{\mathcal{K}}_{f(i,t)} | \text{country set } \mathcal{K}] \end{aligned} \tag{6}$$

Note that the overall contribution can also be decomposed in a parallel way:

$$\begin{aligned} E[\delta^{\mathcal{J}}_{f(i,t)} | \text{country set } \mathcal{J}] - E[\delta^{\mathcal{K}}_{f(i,t)} | \text{country set } \mathcal{K}] = {} & E[\delta^{\mathcal{J}}_{f(i,t)} - \delta^{\mathcal{K}}_{f(i,t)} | \text{country set } \mathcal{K}] \\ & + E[\delta^{\mathcal{J}}_{f(i,t)} | \text{country set } \mathcal{J}] - E[\delta^{\mathcal{J}}_{f(i,t)} | \text{country set } \mathcal{K}] \end{aligned} \tag{7}$$

The average within-firm channel is given by the first line in equations 6 and 7, while the average sorting channel is given by the second line in equations 6 and 7. In the first decomposition (equation 6), the within-firm channel is the difference in country-specific firm pay premium using the distribution of jobs held by workers from country set $\mathcal{J}$, and the sorting channel is the difference in the mean of country set $\mathcal{K}$ firm effects between the jobs held by workers in country set $\mathcal{J}$ and the jobs held by workers in country set $\mathcal{K}$. The alternative decomposition (equation

[14] We drop workers in low-income countries, as these only account for a small percentage of workers.

7) has an analogous interpretation.

The wage premium for a given firm is identified in equation 5 relative to a reference firm. We thus normalize the firm premium so that they are identified relative to a set of firms that provide no premium. While the choice of normalization will affect the within-firm channel estimates, the sorting channel is invariant to the chosen normalization. While Card et al. (2016) use separate data on firm productivity and available surplus (average log value added per worker and sales per worker), we do not observe these measures for firms in our data. In an alternative normalization, Card et al. (2016) normalize all firms in the hotel and restaurant industry to have zero pay premia, as firms in this industry have the smallest wage premiums on average. As we do observe the industries of firms, we follow this and normalize all firms in the lowest-paying industry (in our case, outsourcing) to have pay premium of zero.

5.2 Empirical results

We now discuss the results regarding to what extent firm pay premia in general—and the sorting and within-firm channels in particular—explain wage inequality between workers from high-income countries and workers from non-high-income countries. We begin in the first row of Table 5 by considering the results for all workers. In column (1), we show that the wage gap between workers from these two sets of countries is 0.478.

In columns (2) and (3), we show to what degree workers in each group are found in common firms. While there are 5,108 and 16,250 workers in our relevant analysis sample from high-income and non-high-income countries, respectively, 82.9% and 69.3% of those are also found in the restricted sample of firms that hire workers from both sets of countries, respectively. There is a moderate level of common support of firms across worker country sets.

In column (4), we show that the overall difference in firm premium is 0.241, which is 50.3% of the wage gap. This means that differences in firm-worker matching explains about one half of the wage gap between workers in high-income and non-high-income countries. We then decompose the relative contribution of the sorting and within-firm channels. In columns (5) and (6), we show that the sorting channel explains between 27% and 32% of the overall wage gap, depending on whether we use the firm effects for country set $\mathcal{J}$ or country set $\mathcal{K}$. Finally, in columns (7) and (8), we show that the within-firm channel explains a smaller, but still significant, share of the overall wage gap (between 18% and 23%, depending on whether we use the distribution of jobs held by workers from country set $\mathcal{J}$ or country set $\mathcal{K}$, respectively).

Overall, the sorting of workers from different countries into different firms explains a large share of cross-country wage inequality. Among workers hired through Deel, workers from richer countries are systematically hired by higher-paying firms, potentially reflecting differences in human capital,

Table 5: Contribution of firm pay premium to cross-country wage inequality

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
		Sample sizes			**Decomposition of Firm Component Difference**			
					Sorting		**Within-firm**	
	Overall wage gap	High-income	Non-high-income	Total contribution of firm components	Using high-income effects	Using non-high-income effects	Using high-income distribution	Using non-high-income distribution
All	0.478	4,233	11,269	0.241	0.152	0.130	0.089	0.111
		(82.9)	(69.3)	(50.3)	(31.8)	(27.1)	(18.5)	(23.2)
By experience level:								
Low	0.603	662	1,916	0.241	0.199	0.086	-0.017	0.095
		(83.7)	(64.3)	(30.1)	(32.9)	(14.3)	(-2.9)	(15.8)
Middle	0.469	1,362	4,603	0.219	0.143	0.110	0.076	0.109
		(85.4)	(71.6)	(46.7)	(30.6)	(23.4)	(16.2)	(23.3)
High	0.327	2,209	4,750	0.270	0.141	0.150	0.128	0.120
		(81.1)	(69.4)	(82.5)	(43.2)	(45.9)	(39.2)	(36.6)
By skill level:								
Below-median	0.468	3,937	10,785	0.237	0.154	0.138	0.084	0.100
		(83.0)	(69.1)	(50.7)	(32.9)	(29.4)	(17.9)	(21.3)
Above-median	0.499	296	484	0.283	0.128	-0.081	0.155	0.364
		(81.3)	(74.5)	(56.7)	(25.7)	(-16.3)	(31.1)	(73.1)

Table notes: Wage gaps shown between two country sets: high-income countries and non-high-income countries. Sample size refers to size of connected sets; with the share of overall sample in parentheses. Parentheses in columns (5) through (9) refer to share of overall wage gap. We define low experience as having the seniority variable equal to junior, middle experience as having seniority equal to mid, and high experience as having seniority equal to senior or above. Below-median skill level defined as in occupation with occupation-specific mean wage below the median, and above-median skill level defined analogously.

hiring discrimination, cultural affinity, or other hiring frictions. On the other hand, the differential pay of workers in the same job in the same firm, but from different countries, explains a smaller but still substantial amount of cross-country wage inequality, perhaps due to the presence of only a moderate degree of global wage-setting, as discussed in Section 4.3. Further disentangling the underlying economic mechanisms behind these two channels is important in order to understand the implications of cross-country hiring for human capital investment, firm-side human resources decisions, and other economic policies. However, it will require additional data on workers' characteristics and firms' characteristics and policies that are out of the scope of the present research.

The role of firms by skill levels In the middle and bottom parts of Table 5, we show how the cross-country wage gap and relative contribution of firms vary by the seniority of workers and by the skill-level of worker occupations, respectively. In rows (2) through (4), we show the same decomposition with the same estimated firm fixed effects but separately for workers at different experience levels. We define experience here as three groups: low, middle, and high.[15] In rows (5) and (6), we show the results separately by whether the worker is in a low- or high-skilled occupation. We define the skill-level of the occupation here by the occupation-specific mean wage.

In column (1), we show that the wage gap is largest for less experienced workers and workers in higher-skilled occupations (although the difference is significantly smaller by skill level). In column (4), we see that the firm pay premium matters the most for more experienced workers and workers in higher-skilled occupations. Lastly, while we find that the within-firm channel again plays a smaller role for most worker groups, sorting plays a larger role for most groups, but the largest role for more experienced workers and workers in lower-skill occupations.

6 Surplus from Cross-Country Remote Hiring

In this section, we quantify the gains that cross-country remote hiring creates and how the gains are shared between the workers and firms.

Quantifying the gains from cross-country remote hiring requires data on both the firms' and the workers' outside options. We use data at the country-occupation level from Glassdoor, a website where users report their salaries and experience with their employers. The occupational coverage of Glassdoor aligns well with the occupations represented in cross-country remote hiring. Glassdoor also has global coverage as it operates in many countries around the world (we discuss the data more in Section 2.4). For this exercise, we limit to cross-country relationships for which we can have a reliable estimate for both the worker's and the firm's outside options. Specifically,

[15] In particular, we define low experience as having the seniority variable equal to junior, middle experience as having seniority equal to mid, and high experience as having seniority equal to senior or above.

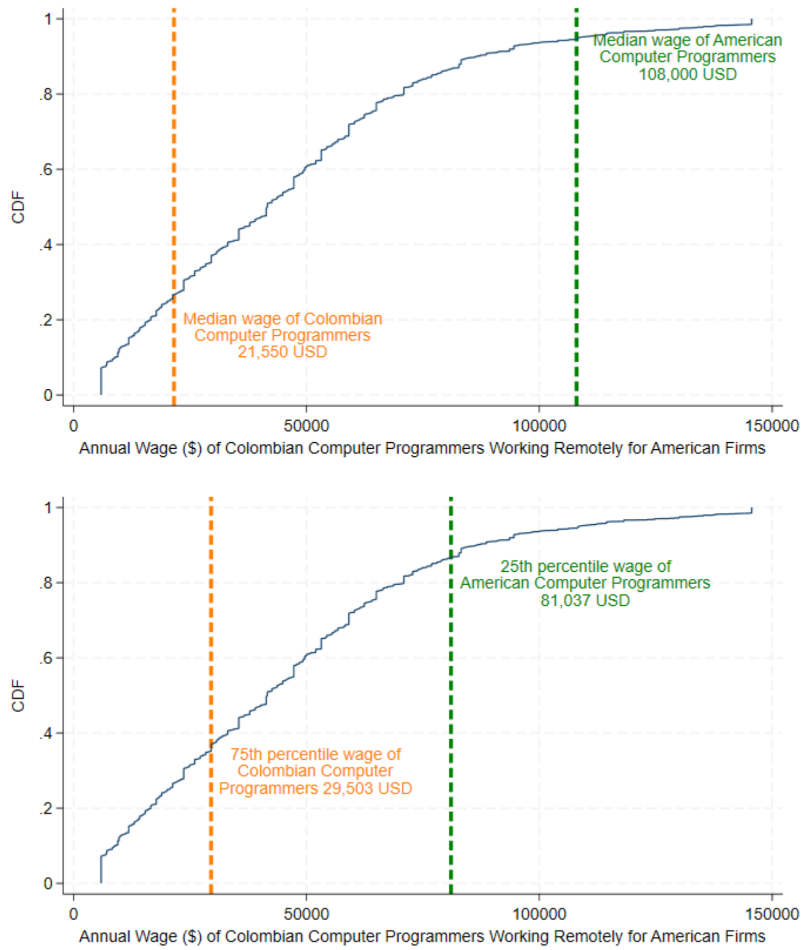

Figure 7: Cross-border vs. domestic wages: an example

we limit to cross-country relationships where there are over 500 salary reports on Glassdoor from 2019 to 2023 under the worker country-occupation pair and under the firm country-occupation pair. In doing so, we are able to match about 31% of contracts in our Deel data set with reliable proxies for outside options. The matched sample slightly over-represents contracts where workers and firms are in high-income countries.[16] The matched sample has a higher wage distribution because Glassdoor has more limited coverage for low-wage occupations.

An Illustrative Example We illustrate how we combine the data on cross-border and domestic wages to estimate the total surplus and its division, as well as the gains for workers and firms. In Figure 7, we compare the distribution of annual wages for Colombian computer programmers

[16] In the matched (unmatched) sample, 37% (34%) of workers are in high-income countries, 37% (40%) in middle-income countries, 26% (26%) in lower middle-income and low-income countries. In the matched (unmatched) sample, 98% (95%) of firms are in high-income countries, 2% (4%) in middle-income countries, and less than 1% (1%) in lower middle-income and low-income countries.

employed by American firms (from Deel data) with the wages of computer programmers in Colombia and computer programmers in the U.S. (from Glassdoor data). Assumptions about the selection of workers and firms into cross-border hiring influence what we consider as their outside options. The top graph assumes that workers and firms engaged in cross-border relationships are representative of their country-occupation group, while the bottom graph assumes positive selection of workers and negative selection of firms—yielding a more conservative surplus estimate.

The median Columbian computer programmer employed by an American firm earns 41,600 USD in Deel's data. The median and 75th percentile computer programmers in Columbia earn 21,550 USD and 29,503 USD, respectively (represented by the orange lines). The median and 25th percentile computer programmers in the U.S. earn 108,000 USD and 81,037 USD, respectively (represented by the green lines). The median surplus of remote hiring between Colombian computer programmers and American firms is therefore $108{,}000 - 21{,}550 = 86{,}450$ USD if we assume neutral selection of workers and firms from their respective country-occupation groups, but $81{,}037 - 29{,}503 = 51{,}534$ USD if we assume a more conservative selection pattern. The median Colombian worker receives $41{,}600 - 21{,}550 = 20{,}050$ USD in surplus, or 24% of the total surplus. The median American firm receives $108{,}000 - 41{,}600 = 66{,}400$ USD in surplus, or 76% of the total surplus. In the next part, we repeat this analysis for each worker country-firm country-occupation.

Bounding surplus Using different outside option proxies, we provide bounds on the median annual surplus created by cross country-hiring in Table 6. The estimates represent the surplus to the firms and workers in the cross-country work relationships if they work together full-time for a year. We note several caveats of our findings. First, our surplus number captures wage differences of workers in different countries and abstracts away from potential non-wage differences such as productivity. If the international, remote workers are less productive than the domestic workers, our estimates for total surplus and firm's gain should be interpreted as upper bounds. Second, we do not consider the potential impact that cross-border remote hiring might have on agents not involved in the hiring, such as the domestic workers in the firm's country. Third, we assume that firms would hire domestically if they did not have the ability to hire remotely, rather than not hire at all. We leave investigation of these important issues to future work. Finally, we note that our surplus figure applies to a single annual contract. To estimate the total gains, such as for workers from a specific country, one must also consider the total number of contracts held by these workers.

If workers and firms in cross-border remote work are representative of their country–occupation, the annualized median total surplus to the worker and firm is about 52,480 USD per contract per year, as shown in column (2) and row (2) of Table 6. Under the same representativeness assumption, workers take home roughly one third of the surplus. Adjusting for purchasing power

Table 6: Median total surplus of cross-country remote hiring (USD per contract per year)

	Firm selection			
	(1)	(2)	(3)	(4)
Worker selection	Firm = 25th	Firm = 50th	Firm = 75th	Firm = own domestic wage
(1) Worker = 25th	Total surplus: \$38,183 Split: 54% w, 46% f Split (ppp): 74% w, 26% f Worker gain: 200% Firm savings: 31%	Total surplus: \$55,036 Split: 41% w, 59% f Split (ppp): 60% w, 40% f Worker gain: 200% Firm savings: 48%	Total surplus: \$84,507 Split: 32% w, 68% f Split (ppp): 50% w, 50% f Worker gain: 200% Firm savings: 60%	Total surplus: \$52,993 Split: 68% w, 32% f Split (ppp): 84% w, 16% f Worker gain: 200% Firm savings: 30%
(2) Worker = 50th	Total surplus: \$34,480 Split: 43% w, 57% f Split (ppp): 70% w, 30% f Worker gain: 110% Firm savings: 31%	Total surplus: \$52,480 Split: 32% w, 67% f Split (ppp): 55% w, 45% f Worker gain: 110% Firm savings: 48%	Total surplus: \$70,111 Split: 26% w, 74% f Split (ppp): 44% w, 56% f Worker gain: 110% Firm savings: 60%	Total surplus: \$47,570 Split: 62% w, 38% f Split (ppp): 80% w, 20% f Worker gain: 110% Firm savings: 30%
(3) Worker = 75th	Total surplus: \$27,745 Split: 29% w, 71% f Split (ppp): 63% w, 37% f Worker gain: 54% Firm savings: 31%	Total surplus: \$46,545 Split: 23% w, 77% f Split (ppp): 48% w, 52% f Worker gain: 54% Firm savings: 48%	Total surplus: \$65,457 Split: 18% w, 82% f Split (ppp): 36% w, 64% f Worker gain: 54% Firm savings: 60%	Total surplus: \$39,256 Split: 54% w, 46% f Split (ppp): 78% w, 22% f Worker gain: 54% Firm savings: 30%

Table notes: Total surplus assumes worker works full-time for one year at given wage. Split refers to percentage of overall surplus received by worker (w) and firm (f). Split (ppp) adjusts the percentage of overall surplus by purchasing power differences between the worker country and the firm country. Worker gain and firm savings are relative to their estimated domestic outside options, respectively. "Firm = 25th" refers to the assumption that the firms in our data set are negatively selected, in particular that the 25th percentile domestic wage is a good proxy for the outside option of the median firm in our data. In the column "Firm = own domestic wage", we use the observed domestic wages (only available for selected firms) in our data set to proxy for the firms' outside options.

parity (PPP), workers and firms roughly split the surplus (55% for workers, 45% for firms).[17] We bound the median surplus between 27,745 and 84,507 USD per contract per year, depending on the type and amount of selection of the firm and worker.[18] Firms and workers both gain significantly in cross-country hiring, with workers' gains ranging from $54\%-200\%$ and firms' gains ranging from $30\%-60\%$, depending on the respective proxies for their domestic outside options. The split differs substantially depending on the outside option proxies for workers and firms, with workers estimated to take between $36-84\%$ of the total gains after accounting for PPP.

The influence of occupation and countries We next investigate how the surplus split, worker's gain, and firm's gain depend on the occupation, worker's country, and firm's country. We estimate the below specification at the contract level

$$Y_{ijoc}=\alpha_1\ln(\text{GDP per capita}_i)+\alpha_2\ln(\text{GDP per capita}_j)+\alpha_3(\text{Skill}_o)+\epsilon_{ijoc}, \tag{8}$$

where i is the worker's country, j is the firm's country, o is the occupation, and c is a contract. For the skill of an occupation we use the log Glassdoor median wage for American workers in that occupation. We run the regression for four outcome variables: worker's share of the surplus, worker's PPP-adjusted share of the surplus, worker's gain, and firm's gain. We report the results in Table 7.

Controlling for the firm's country and occupation, workers from wealthier countries capture a larger share of the surplus generated by cross-border remote work, regardless of PPP adjustments. However, workers from wealthier countries experience a smaller proportional gain in cross-country remote work—measured as the percentage increase in wages compared to their domestic alternatives. These findings are in keeping with the wage patterns we explored in Section 4. Workers from higher-income countries earn more than workers in lower-income countries in the global labor market, capturing a larger share of the surplus generated. However, this advantage is not sufficient to result in a greater wage increase compared to their domestic opportunities. Finally, workers in more skilled occupations claim a higher share of the surplus and experience a larger proportional wage gain.

Firms' proportional wage savings—defined as the percentage wage savings relative to hiring domestically—are greater for firms hiring workers in lower-income countries, for firms based in higher-income countries, and for firms that hire in lower-skilled occupations. Firms' wage savings and workers' wage gains are only one aspect of the benefits derived from global hiring. Other advantages, such as foreign workers' contributions to expansion into new markets and the enhanced job flexibility for employees could be particularly salient in the context of white-collar jobs but

[17] We use 2019 PPP data from Penn World Table version 9.1. Because workers tend to be located in countries with larger purchasing power, adjusting for PPP increases the relative share that the workers receive.

[18] We note that part of the surplus goes to the intermediary, the HR company Deel. Deel charges firms $600 a year for hiring a contractor and $7,200 for hiring an employee. Accounting for the intermediary's share implies a smaller share of the surplus and smaller gains for the firms.

are not examined in this paper due to data limitations.

Table 7: The influence of occupation and countries on surplus split and gains

	Worker's share	Worker's PPP-adjusted share	Worker's gain	Firm's gain
$\ln(\text{pcGDP}_i)$	0.307***	0.195***	-0.174***	-0.247***
	(0.003)	(0.003)	(0.006)	(0.002)
$\ln(\text{pcGDP}_j)$	-0.322***	-0.156***	0.180***	0.373***
	(0.010)	(0.009)	(0.020)	(0.006)
$\ln(\text{US wage}_o)$	0.147***	0.155***	0.323***	-0.161***
	(0.007)	(0.006)	(0.015)	(0.004)

Table notes: Sample is winsorized at the 5th and 95th percentiles of the outcome variables to avoid errors in wages biasing the results. Standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

The relationships observed in Table 7 are not mechanically driven; rather, they emerge from empirical patterns in cross-border wages. For instance, in a hypothetical wage-setting model where firms pay workers the same wage regardless of their country of residence, workers from richer countries would receive a smaller share of the total surplus—opposite to our findings in Table 7. Alternatively, consider a wage-setting model in which firms pay workers precisely what they would earn domestically. In this case, workers' gains would be uniform across countries, rather than decreasing with the income level of their home country.

7 Concluding Remarks

Using a novel and large-scale data set on firms and their remote international workers, we provide one of the first micro-analyses on the phenomenon of international remote hiring. Cross-border, remote hiring allows firms and workers to collaborate without having to physically move or migrate, presenting important opportunities for trade, development, and labor markets alike.

Our findings offer a nuanced picture of cross-border hiring. In the first section, we find that the preferences for where to hire depend on the skill requirements of the occupations. In the second section, we find that wages are more equal across countries in cross-border hiring compared to in domestic hiring, suggesting that cross-border hiring can potentially reduce wage inequality. We explore the remaining wage inequality and attribute a large part of it to the role of firms. We find that the sorting of workers from high-income countries to high-paying firms, in addition to wage differences within firms, explains a substantial part of the remaining wage inequality.

In the third and final section, we quantify the overall gains of cross-country hiring with a simple exercise of comparing the wages in cross-border remote hiring to the firms' and workers' respective domestic outside options. We show that both workers and firms benefit from cross-border remote work, and provide bounds to account for potential selection into such cross-border remote work.

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A Appendix Tables

Table A1: Gravity estimates of cross-country hiring: alternative specifications

	Number of Contracts			
	OLS	PPML($y>0$)	PPML	PPML
Population in worker country (log)	0.321***	0.593***	0.637***	-0.317**
	(0.013)	(0.046)	(0.040)	(0.147)
Population in firm country (log)	0.259***	0.881***	0.922***	0.905***
	(0.011)	(0.059)	(0.054)	(0.064)
GDP per capita in worker country (log)	0.165***	0.196***	0.238***	
	(0.019)	(0.067)	(0.062)	
GDP per capita in firm country (log)	0.779***	1.770***	2.025***	1.890***
	(0.025)	(0.155)	(0.144)	(0.159)
Labor supply in worker country (log)				0.964***
				(0.160)
Distance (log)	-0.244***	-0.170	-0.132	-0.084
	(0.037)	(0.219)	(0.216)	(0.261)
Time difference (absolute value)	-0.016	-0.054	-0.058	-0.038
	(0.011)	(0.080)	(0.075)	(0.081)
Common language	0.808***	1.372***	1.562***	1.682***
	(0.054)	(0.221)	(0.221)	(0.271)
Observations	4,088	4,088	20,627	10,926
Firm countries	140	140	140	140
Worker countries	195	195	195	195

Table notes: First and second columns display results using only country pairs that have non-zero hires. Third and fourth columns include country pairs with zero hires as long as the firm country and the worker country have non-zero hires with some other country in our data set. We think these pairs are plausible options insofar as our data provider operates in these countries, and therefore zero hires between these countries are meaningful. Labor supply in worker country is the workforce in remote-able occupations that we construct from ILO data. We drop the GDP per capita in worker country in the fourth column because it is highly collinear with the population in worker country and the labor supply in worker country. Standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table A2: Gravity estimates of cross-country hiring: total remuneration as outcome

	Amount of remuneration			
	OLS	PPML($y>0$)	PPML	PPML
Population in worker country (log)	0.348***	0.312***	0.366***	-0.762***
	(0.022)	(0.014)	(0.009)	(0.046)
Population in firm country (log)	0.280***	0.315***	0.264***	0.262***
	(0.019)	(0.017)	(0.010)	(0.014)
GDP per capita in worker country (log)	0.531***	0.352***	0.382***	
	(0.032)	(0.023)	(0.014)	
GDP per capita in firm country (log)	1.159***	0.928***	1.022***	0.979***
	(0.043)	(0.042)	(0.021)	(0.026)
Labor supply in worker country (log)				1.108***
				(0.046)
Distance (log)	-0.245***	-0.226***	-0.112***	-0.118***
	(0.064)	(0.045)	(0.027)	(0.037)
Time difference (absolute value)	-0.070***	-0.011	-0.078***	-0.075***
	(0.020)	(0.014)	(0.008)	(0.010)
Common language	0.886***	0.555***	0.453***	0.589***
	(0.094)	(0.056)	(0.043)	(0.052)
Observations	3,953	4,088	20,627	10,926
Firm countries	140	140	140	140
Worker countries	195	195	195	195

Table notes: First and second columns display results using only country pairs that have non-zero hires. Third and fourth columns include country pairs with zero hires as long as the firm country and the worker country have non-zero hires with some other country in our data set. We think these pairs are plausible options insofar as our data provider operates in these countries, and therefore zero hires between these countries are meaningful. Labor supply in worker country is the workforce in remote-able occupations that we construct from ILO data. We drop the GDP per capita in worker country in the fourth column because it is highly collinear with the population in worker country and the labor supply in worker country. Standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table A3: Elasticity of wage to local labor market conditions: using GDP per capita

	Hourly wage (log)				
	(1)	(2)	(3)	(4)	(5)
GDP per capita in worker country (log)	0.266***	0.131***		0.273***	0.255***
	(0.003)	(0.002)		(0.003)	(0.003)
GDP per capita in firm country (log)	0.163***		0.145***	0.189***	0.167***
	(0.004)		(0.004)	(0.005)	(0.004)
Observations	99,628	95,325	99,617	67,588	92,081
Adjusted R-squared	0.291	0.680	0.357	0.435	0.335
Controls	Y	Y	Y	Y	Y
Firm FE		Y			
Worker country FE			Y		
Occupation FE				Y	
Industry FE					Y

Table notes: Sample is limited to fixed contract workers. Controls include worker seniority, start month and year of contract, and contract pay frequency. Standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table A4: Elasticity of PPP-adjusted wage to local labor market conditions: using GDP per capita

	Hourly wage (log, adjusted for purchasing power parity)				
	(1)	(2)	(3)	(4)	(5)
GDP per capita in worker country (log)	-0.066***	-0.202***		-0.054***	-0.077***
	(0.003)	(0.003)		(0.003)	(0.003)
GDP per capita in firm country (log)	0.153***		0.144***	0.180***	0.157***
	(0.004)		(0.004)	(0.005)	(0.004)
Observations	99,443	95,143	99,434	67,464	91,917
Adjusted R-squared	0.206	0.641	0.315	0.378	0.257
Controls	Y	Y	Y	Y	Y
Firm FE		Y			
Worker country FE			Y		
Occupation FE				Y	
Industry FE					Y

Table notes: Sample is limited to fixed contract workers. Controls include worker seniority, start month and year of contract, and contract pay frequency. Standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table A5: Elasticity of wage to local labor market conditions: all workers

	Hourly wage (log)				
	(1)	(2)	(3)	(4)	(5)
Median occupation-specific wage	0.608***	0.391***	0.359***	0.594***	0.584***
in worker country (log)	(0.004)	(0.004)	(0.011)	(0.004)	(0.005)
Median occupation-specific wage	0.185***	0.110***	0.237***	0.191***	0.149***
in firm country (log)	(0.006)	(0.009)	(0.008)	(0.009)	(0.007)
Observations	62,683	57,883	62,683	62,683	58,129
Adjusted R-squared	0.469	0.743	0.488	0.480	0.484
Controls	Y	Y	Y	Y	Y
Firm FE		Y			
Worker country FE			Y		
Occupation FE				Y	
Industry FE					Y

Table notes: Sample is not limited to fixed contract workers and instead includes all workers. Controls include worker seniority, start month and year of contract, contract pay frequency, and contract type. Standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table A6: Elasticity of wage to local labor market conditions: using GDP per capita, all workers

	Hourly wage (log)				
	(1)	(2)	(3)	(4)	(5)
GDP per capita in worker country (log)	0.433***	0.269***		0.416***	0.422***
	(0.002)	(0.002)		(0.002)	(0.002)
GDP per capita in firm country (log)	0.124***		0.112***	0.154***	0.127***
	(0.004)		(0.003)	(0.004)	(0.004)
Observations	179,109	171,374	179,100	119,672	166,300
Adjusted R-squared	0.392	0.690	0.475	0.485	0.423
Controls	Y	Y	Y	Y	Y
Firm FE		Y			
Worker country FE			Y		
Occupation FE				Y	
Industry FE					Y

Table notes: Sample is not limited to fixed contract workers and instead includes all workers. Controls include worker seniority, start month and year of contract, contract pay frequency, and contract type. Standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table A7: Elasticity of PPP-adjusted wage to local labor market conditions: using GDP per capita, all workers

	Hourly wage (log, adjusted for purchasing power parity)				
	(1)	(2)	(3)	(4)	(5)
GDP per capita in worker country (log)	-0.096***	-0.068***		-0.081***	-0.084***
	(0.002)	(0.002)		(0.002)	(0.002)
GDP per capita in firm country (log)	0.103***		0.112***	0.134***	0.108***
	(0.004)		(0.003)	(0.004)	(0.004)
Observations	178,861	171,136	178,855	119,508	166,080
Adjusted R-squared	0.191	0.591	0.329	0.340	0.234
Controls	Y	Y	Y	Y	Y
Firm FE		Y			
Worker country FE			Y		
Occupation FE				Y	
Industry FE					Y

Table notes: Sample is not limited to fixed contract workers and instead includes all workers. Controls include worker seniority, start month and year of contract, contract pay frequency, and contract type. Standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table A8: Elasticity of wage to local labor market conditions: by skill level

	Hourly wage (log)		
	All	By Skill level	
		Lower-Skilled	Computer Programmers
	(1)	(2)	(3)
Median occupation-specific wage	0.384***	0.447***	0.308***
in worker country (log)	(0.005)	(0.008)	(0.007)
Median occupation-specific wage	0.338***	0.151***	0.203***
in firm country (log)	(0.008)	(0.017)	(0.012)
Observations	33,231	11,205	22,016
Adjusted R-squared	0.391	0.401	0.293
Controls	Y	Y	Y

Table notes: Sample is limited to fixed contract workers. Controls include worker seniority, start month and year of contract, and contract pay frequency. Skill level of occupation defined by tercile of mean occupation-specific wage. Standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table A9: Wage variation

	Entire sample		Switchers sample	
	Standard deviation	Variation explained	Standard deviation	Variation explained
	(1)	(2)	(3)	(4)
Controls	21.64	-	19.66	-
Firm country	21.11	3%	19.27	2%
Firm ID	13.88	36%	12.03	39%
Occupation	13.59	37%	11.72	40%
Worker country	12.38	43%	11.27	43%
Worker ID	6.15	72%	6.15	69%
Observations	233,299		56,140	

Table notes: The first pair of columns include the entire sample of workers. The second pair of columns is limited to the sample of workers that we observe in more than one firm. Controls include the contract type, contract start year and month, seniority level, and pay frequency.

B Data Appendix

B.1 Variable construction

The data contains the following variables, from which we derive our main hourly wage and total earnings variables.

- `latest_rate`: Latest wage rate paid to worker, in currency of choice
- `latest_currency`: Currency of choice
- `latest_scale`: Frequency (e.g., hourly, daily, weekly, biweekly, monthly, semimonthly, custom) of how often `latest_rate` is paid
- `sum_amount_invoiced`: Total amount paid to worker

We then consider two main outcomes:

1. Hourly wage rate:
   (a) For EOR: Use wage rate implied by total amount earned and start and end date of contract. Assume that workers are full-time and thus work 176 hours per month.
   (b) For Fixed Contracts: Use wage rate implied by `latest_rate` and `latest_scale`.
   (c) For PAYG Contracts: Use wage rate implied by `latest_rate` and `latest_scale`.
   (d) For Milestone Contracts: Since these workers are paid for these contracts when they reach a milestone, the `latest_scale` variable is missing. We thus use the wage rate implied by the total amount earned and start and end date of contract, and assume full-time work.

   Using this procedure we are able to compute an hourly wage rate for 57%, or 280,000, of the contracts that have a positive total payment (`sum_amount_invoiced`). The vast majority of the contracts for which we are not able to compute an hourly rate are PAYG contracts, which do not have a latest rate variable.
2. Total earnings: This is simply given by `sum_amount_invoiced`.