

Remote Multinationals: Wage Compression and Worker Sorting in Cross-Country Remote Work

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Abstract

We provide empirical evidence on wage-setting and worker sorting in a new form of hiring: firms hiring remote workers abroad without physical establishments. Examining human resources data covering 20,000 firms and 200,000 internationally hired remote workers across 195 countries, we show that cross-country wage differences among remotely hired international workers are smaller than those in traditional domestic labor markets. Exploiting exchange rate shocks, we find that wages are anchored to pay at firms' headquarters. Nonetheless, cross-country wage disparities persist, with a large share explained by differential sorting of workers into firms. Differences in human capital are associated with this sorting.

JEL Codes: F23, F66, J31, J61.

Keywords: multinational firms; remote work; international hiring; wage structure.

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1 Introduction

Multinational firms have long employed workers across countries, traditionally through foreign subsidiaries, plants, and offices. The canonical model of global production is one of workers employed in physical establishments around the world (Antràs and Yeaple (2014)). As advances in telecommunications technology and the growth of service-sector work have made remote work increasingly feasible, firms can now hire workers across countries without establishing a physical presence abroad (Baldwin and Dingel (2022); Blinder (2009); Dingel and Neiman (2020)). In effect, firms can become remote multinationals—globally-distributed organizations connected through digital technologies rather than foreign establishments.

Remote multinationals may or may not set wages in the same way as multinational firms with foreign establishments (Hjort et al. (2026a,b); Minni (2024)). On one hand, remote work may integrate workers across countries into a common organization. Workers may perform complementary tasks and interact with the same colleagues and managers, potentially increasing pressure for firm-wide wage-setting and compressing wage differences across countries (Bloom (2023)). On the other hand, remote work may weaken workers’ attachment to the firm, leading firms to benchmark compensation more closely to workers’ local outside options (Grossman and Rossi-Hansberg (2008)).

Standard labor market data are poorly suited to studying these questions because censuses and administrative records generally do not link workers employed by the same firm across countries. Previous work has instead studied workers within individual countries (Hjort et al. (2026b)) or used proprietary personnel data linking workers across countries (Hjort et al. (2026a); Minni (2024)). However, this literature has focused on traditional multinationals with physical establishments abroad rather than firms employing workers remotely across countries.

We use administrative data from Deel, a large global payroll and human resources company that facilitates cross-country remote hiring. Deel acts as an employer of record and provides contractor services, among other services, allowing firms to hire workers abroad without establishing a local entity. The data cover over 20,000 firms and 200,000 international remote workers across 195 countries, covering work relationships between 2021 and 2023. Because firms typically hire workers located in multiple countries, we can compare wages across workers employed by the same firm, often also in the same occupation. For a subset of firms, we additionally observe wages paid to domestic workers, allowing us to study whether wages paid to remote international workers are anchored to wages in the firm’s headquarters. Finally, we combine these data with occupation-level wage information from Glassdoor to benchmark wages to local labor market conditions.

This paper begins with descriptive evidence of the relationship between the wages of international remote workers and the wages in the workers’ and firms’ local labor markets. The elasticity of wages with respect to average wages in the same occupation in the worker’s country is 0.37, while the elasticity

with respect to wages in the same occupation in the firm’s country is 0.34. The elasticity with respect to wages in the worker’s country is lowest for the highest-skilled occupations. On the other hand, the elasticity with respect to wages in the firm’s country is largest for the highest-skill occupations. Thus, remote wages overall remain tethered to a worker’s local conditions, but cross-country wage differences are substantially compressed relative to those observed in domestic labor markets.

Including firm fixed effects decreases the elasticity with respect to wages in the worker’s country by 50%. This suggests that cross-country wage differences are smaller within firms than across firms. This pattern could reflect clustering of similarly skilled workers in firms or a firm-wide wage-setting practice driven by norms or other reasons. To distinguish between these explanations, we follow [Hjort et al. \(2026b\)](#) and use exchange rate shocks to estimate how changes in a firm’s headquarters wages affect wages of its remote workers abroad. A 1% increase in headquarters wages induced by exchange rate movements raises remote workers’ wages by 0.37%, providing evidence of firm-wide wage-setting norms in remote multinationals.

However, wage compression within firms does not eliminate wage differences between workers in different countries. We therefore turn to the role of worker sorting across firms in generating cross-country wage differences in remote multinationals. We quantify the degree to which wage differences between workers from high-income and middle-income countries are due to firm pay premia, which include two channels—the sorting of workers into firms and within-firm pay differences. Overall, differences in firm pay premia account for over half of the average wage difference between workers from high-income countries and workers from middle-income countries. Moreover, most of this component is driven by sorting: workers from high-income countries are disproportionately employed by higher-paying firms. This result complements the earlier firm-fixed-effects evidence by showing that firm sorting is an important source of cross-country wage differences in remote work.

We conclude with suggestive evidence that this sorting into firms is related to differences in human capital: workers in higher-skilled occupations, with more experience, and who live in more educated countries sort into firms with significantly greater pay premia. While only descriptive, this suggests that differences in human capital across workers from different countries might be an important factor in explaining worker-firm sorting and ultimately wage-setting in international remote work. These findings have implications for workers, firms, and governments hoping to benefit from opportunities created by remote work (e.g., [ILO \(2021\)](#)): while remote work can offer access to high-paying firms abroad, cross-country differences in human capital may limit how far it can expand that access.

Relation to the literature The primary contribution of this paper is to provide empirical evidence on wage-setting practices and the role of firms in a new labor market. First, this paper relates to the literature on wage-setting practices in multinational firms ([Hazell et al. \(2022\)](#); [Hjort et al. \(2026a,b\)](#); [Minni \(2024\)](#)), in addition to related studies on firm-wide wage-setting practices in a domestic context ([Hazell](#)

et al. (2022)) and among temp workers and outsourced workers (Drenik et al. (2023); Goldschmidt and Schmieder (2017)).¹ It is well-documented that firms with foreign establishments are disproportionately large: U.S.-owned multinationals employ more than 4,000 workers on average, compared with 19 at non-multinationals (Kamal et al. (2022)). By reducing the fixed costs of establishing a foreign presence, remote hiring may allow more firms to engage directly in cross-country employment. We contribute to this literature by showing that similar cross-country wage compression exists in remote multinationals, while also highlighting the importance of worker-firm sorting.

Second, our setting is related to online marketplaces connecting employers with international gig workers (e.g., Agrawal et al. (2015); Brinatti et al. (2021); Fernando et al. (2023); Horton et al. (2017); Stanton and Thomas (2025)).² The relationships we study, however, more closely resemble steady employment: jobs last six months on average, compared with 71 hours in Stanton and Thomas (2025). The scale of this activity is already substantial: Deel processed roughly five times as much payroll as Upwork, the leading online gig-work platform, in 2024 (\$20 billion versus \$4 billion; Deel (2024); Upwork Inc. (2025)). We build on Brinatti et al. (2021) by showing that international remote workers' wages are linked not only to local labor market conditions but also to firm-wide wage-setting practices.

Lastly, our paper is related to the literature on high-skilled migration and international job-posting (e.g., Amanzadeh et al. (2024); Clemens (2013); Kerr et al. (2016, 2015); Mahajan et al. (2024); Muñoz (2024)). While workers historically have had to move to access firms located in different countries, remote work has the potential to connect workers and firms across borders without physical migration.³

2 Context and Data

2.1 Context

It is difficult for firms to hire workers in countries where the firm has no legal presence. Traditionally, temporary employment agencies and staffing firms, as in Drenik et al. (2023), have facilitated such hiring. They recruit workers on their roster and place them with clients. In recent years, a new type of firm has emerged. They own legal entities across the world and act as the worker's legal employer after the client firm recruits and selects the worker themselves. These firms often also provide contractor services as well as handle payroll, taxes, compliance, benefits, and other services related to global human resources. Recent estimates suggest that the size of this market surpassed one million workers in 2023 (Dahan (2024)).

Deel is one such global payroll and human resources company. It operates in over 150 countries and pays workers in over 120 currencies. The latest estimate from Deel is that it facilitates 22 billion USD

¹Theoretical work on trade in tasks has considered the potential for remote work: Grossman and Rossi-Hansberg (2008); Ottaviano et al. (2013); Rodríguez-Clare (2010).

²More broadly, we contribute to the recently-growing literature on remote work (e.g., Barrero et al. (2023)) by considering how remote technologies affect firm hiring and worker's labor market opportunities internationally.

³Related work also studies wage-setting for immigrants (Amior and Stuhler (2023); Dostie et al. (2023); Naidu et al. (2016)).

in annual payroll, supporting over 40,000 firms and 1.5 million workers globally, including workers hired locally ([Thompsett \(2025\)](#)). For comparison, there are currently about 400,000 workers on H-1B visas in the United States ([USCIS \(2025\)](#)). Overall, these statistics suggest that the scale of cross-country remote hiring is economically meaningful, despite receiving little attention thus far.

2.2 Data description

Data from Deel 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, the data includes the start and end dates, the pay rate and pay frequency, the overall pay, the currency used, the job title, the worker’s location, and the experience level of the worker, indicated by ten levels. Note that we only observe the end date if the contract is complete.

Firm characteristics include firm industry, size, and location. Importantly, the data also includes a unique identifier for the firm and a unique identifier for the worker, allowing us to link different workers within a firm. See [Appendix C](#) for more information on the data, including how the hourly wage variable is constructed and sample restrictions. Most of the paper focuses on fixed term contracts, because the wage data is most reliable for these workers, as described in [Appendix C](#). Fixed term contract workers make up a majority of the sample (55% of the overall sample). Robustness checks, as discussed, suggest that the main findings are similar for other types of workers as well.

Other data We complement the data from Deel with external data. First, we use external wage data at the country-occupation level. Obtaining standardized occupation-level wage data across countries can be challenging. One commonly-used data source, the Occupational Wages around the World database ([Freeman and Oostendorp \(2002\)](#)) ends ten years before the start of Deel’s data and uses an occupational classification from 1988 that does not provide sufficient coverage of service-sector jobs that can be conducted remotely. We therefore use data from another source, namely Glassdoor, an American website that collects self-reported company reviews and salaries from workers around the world, covering 2019 to 2023. To ensure data quality, we use country-occupation pairs that have at least 500 salary observations in the observation period. [Appendix C.3](#) further explores the validity of the Glassdoor data. Second, we use data on exchange rates from the OECD Exchange Rates database. Finally, we use the country classification from the World Bank that divides countries into four groups: high-income, upper middle-income, lower middle-income, and low-income.

2.3 Summary statistics

Table 1 reports summary statistics at the contract-, worker-, and firm-level. The sample includes over 200,000 contracts in total, where the median realized contract length is 5 months with an hourly wage rate of 16.52 USD. Nearly all (92%) contracts represent cross-country relationships, while the majority (63%) further represent intercontinental relationships. Note that only 21% of contracts have been completed, with the rest ongoing. This suggests that the intended contract length is likely longer than the median realized length of 5 months; in fact, contracts that started in 2022 or earlier, for example, have realized median contract lengths of 9 months.⁴

There are over 200,000 workers in the sample. 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. Lastly, the sample includes over 20,000 firms in total. The sample includes both a large amount of small firms and a small amount of large firms. The average firm hires 11 workers—10 of which are international workers—from 4 unique country-occupation combinations (e.g., software engineer in Argentina).⁵

This section concludes by considering the location, occupation, and industry distributions of the work relationships.⁶ 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, 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, and Germany. 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.⁷

3 Cross-Country Wage Compression in Remote Hiring

This section considers how the wages of remote workers around the world compare to the wages in their local labor markets in the same occupation. To investigate the relationship between local wages and wages in the global remote labor market, we estimate the following equation:

$$\log w_{ijoc} = \gamma_1 \log(\text{median wage}_{io}) + \gamma_2 \log(\text{median wage}_{jo}) + \gamma_3 X_{ijoc} + \epsilon_{ijoc} \quad (1)$$

⁴54% of contracts started in 2022 or earlier. Further, of the contracts that started in 2021 or earlier, the realized median contract length is 11 months.

⁵While these data include only workers hired through Deel, firms likely use Deel for almost all of their cross-country hiring, given the challenges of hiring internationally without such a service.

⁶These results are not explicitly reported for data confidentiality purposes.

⁷The most common country-occupation combinations are software developers in Argentina, software developers in Brazil, and software developers in India. International remote workers in the data make up approximately 8.0%, 0.7%, and 0.1% of the total number of software developers in each country, respectively ([International Labour Organization \(2026\)](#)). While large general equilibrium effects due to international remote hiring are unlikely, growth in international remote hiring suggests that they may soon become important to consider.

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 , median wage _{io} is the median wage in the same occupation o in the same worker country i collected by Glassdoor, median wage _{jo} is the median wage in the same occupation o but in the firm's country j , and X_{ijoc} are various controls (worker experience level, start month and year of contract, and contract pay frequency). We also estimate versions of Equation (1) with various fixed effects. If local labor markets are fully competitive, then wages should converge to the local market-clearing rate regardless of the hiring firm, implying a slope of one on the worker's country wage and zero on the firm's country wage, as in the trade-in-tasks framework of [Grossman and Rossi-Hansberg \(2008\)](#).

Column (1) of Table 2 shows that local wage differences are transmitted only partially to workers employed remotely by foreign firms.⁸ A 10% difference in local labor market wages corresponds to a 4.1% difference in wages for remotely hired workers. Similarly, workers who are employed by firms in higher-income countries are paid more (the elasticity of remote wages to the firm country's local wage level in 0.37). Column (2) shows a small dampening of the relationship between local labor market wages and remote wages when including worker and contract controls. Column (3) includes firm fixed effects and shows that remote wages are significantly less elastic to local labor market wages when considering workers in the same firm but that work in different countries. The elasticity decreases by 53%, from 0.374 to 0.166, suggesting that most of the wage premium associated with higher-paying local labor markets reflects workers sorting into higher-paying firms, even within occupations.⁹

Comparison to other contexts Table A2 uses the GDP per capita in the worker and firm countries as regressors instead of the occupation-level median wages, allowing us to directly compare our estimate with those in related settings. The elasticity with respect to GDP per capita is generally smaller than that with respect to occupation-level wages.¹⁰ Because occupation-specific wages are likely to more closely capture the local labor market conditions relevant to a worker's outside option, estimates based on GDP per capita may bias the true relationship between local labor market conditions and wages.

The elasticity of 0.271 in our setting is similar to that estimated by [Hjort et al. \(2026a\)](#) (0.258) in their context of large, traditional multinationals and that estimated by [Brinatti et al. \(2021\)](#) (0.23) in their context of an online gig work platform. When including firm fixed effects, the elasticity in Table A2 decreases by 45% to 0.148, while the estimate in [Hjort et al. \(2026a\)](#) decreases by only 7% to 0.22. The significantly smaller within-firm elasticity in our case suggests that firm sorting plays a substantially

⁸The smaller sample size is due to the limited coverage of the Glassdoor data and the restriction to fixed contract workers. The complete sample (about 218,000 workers) is included when considering the elasticity with respect to the GDP per capita of the worker's and firm's countries for all workers, in Table A3. Table A3 shows that the elasticities are slightly larger when considering all workers, but exhibit the same qualitative patterns that we discuss when limiting to fixed contract workers.

⁹Table A1 reports the results of a standard wage variance decomposition and shows that firms explain the largest share of wage variation among any covariates, including occupation and worker location.

¹⁰Table A4 replicates the analysis with GDP per capita but limits the sample to workers that also have corresponding Glassdoor data, and finds similar results (main elasticity of 0.258). This implies that the differential Glassdoor data coverage does not explain the difference in elasticity magnitudes.

larger role in generating wage differences when workers collaborate remotely than when they are hired into different physical establishments of multinational firms.

One potential explanation of this difference between these two contexts is that remote workers interact more frequently with coworkers in other countries than workers in different physical establishments of the same multinational firm do. Greater cross-country interaction may increase the salience of within-firm pay differences and thus create greater pressure for firm-wide wage-setting across countries (Cullen and Pakzad-Hurson (2023); Hazell et al. (2022)). Consistent with this mechanism, Figure A1 shows that the within-firm elasticity of wages to local labor market conditions is substantially smaller when firms hire workers in the same occupation across multiple countries. This relationship is unchanged after controlling for the number of workers employed by the firm in that occupation.

Heterogeneity Table 2 also investigates how the wage elasticity depends on the skill level of the occupation, by estimating Equation (1) separately for two groups of occupations, given their average wage level.¹¹ Columns (4) through (7) show that the elasticity of wages with respect to local labor market conditions in the worker’s country is decreasing in the skill level of the occupation, which is consistent with Hjort et al. (2026a). In other words, wages are less tethered to local conditions in higher-skilled occupations. Conversely, the relative importance of labor market conditions in the firm’s country is increasing in the occupation’s skill level, consistent with Minni (2024). We contribute to Hjort et al. (2026a) and Minni (2024) by showing that the negative relationship between occupational skill level and the importance of workers’ local labor market conditions extends to remote work. Moreover, Table 2 shows that firm sorting plays a substantially larger role among higher-skilled occupations, accounting for 54% of the relationship between local wages and remote wages, compared with 16% among lower-skilled occupations. Finally, Table A5 shows that the pattern is similar across workers of varying experience levels: the elasticity with respect to local labor market conditions is smallest for the most experienced workers, for whom firm sorting also plays the largest role.

4 Anchoring of Remote Wages to Headquarters Wages

In the previous section, we show that wages of workers located in different countries are more similar within firms than across firms. This pattern could arise for several reasons, including the sorting of workers with similar human capital into the same firms or unobserved firm-level productivity shocks. In this section, we examine whether another mechanism contributes to this pattern: firms may anchor the wages of their international remote workers to wages at their headquarters. While Hjort et al.

¹¹The uneven sizes of the two occupation groups is due to the large number of software engineers in the sample. When we consider the elasticity with respect to the GDP per capita of the worker’s and firm’s countries, software developers make up a smaller share of the sample. The most common occupation in the above-median group in this exercise is software engineers, while the most common occupations in the below-median group are customer support and sales.

(2026b) document wage anchoring within traditional multinational firms, we investigate whether a similar practice exists among remote multinationals.

We begin by estimating the relationship between wages paid to a firm’s international remote workers and wages paid to its domestic workers:

$$\log w_{cfijt} = \beta \cdot \log(\text{Wage in HQ}_{fjt}) + \gamma x_{it} + \delta_f + \delta_{it} + \epsilon_{cfijt}, \quad (2)$$

where $\ln w_{cfijt}$ is the log wage in US dollars in contract c between firm f , headquartered in country j , and a remote worker in country i , with a contract beginning in month t . Wage in HQ $_{fjt}$ is the average wage in USD paid by firm f to newly hired domestic workers in its headquarters country j in month t ; x_{it} is the exchange rate between the worker country’s currency and USD in month t ; δ_f denotes firm fixed effects; and δ_{it} denotes worker country $\times$ year fixed effects. The coefficient of interest, β , captures the within-firm relationship over time between wages paid to domestic workers and those paid to international remote workers, net of changes in exchange rates and broader economic conditions in the worker’s country.

Estimating Equation (2) additionally requires observing both a new remote hire and a new hire in the firm’s home country by the same firm in the same month, substantially reducing the sample size. Column (4) of Table 3 reports the results. There is a positive relationship between wages paid to foreign remote workers and contemporaneous wages paid to workers at the firm’s headquarters.

This relationship alone, however, does not establish that firms anchor foreign wages to headquarters wages. To investigate wage anchoring, we follow Hjort et al. (2026b) and exploit plausibly exogenous variation in headquarters wages generated by exchange-rate movements in the firm’s headquarters country. Exchange-rate movements can potentially change headquarters wages measured in US dollars, but foreign remote workers are not directly exposed to those same currency shocks. If firms anchor foreign workers’ wages to headquarters wages, exchange-rate-induced changes in headquarters wages would pass through to the wages of foreign remote hires.¹²

We implement this test in three steps. Column (1) establishes the first stage relationship between the exchange rate in the headquarters country and wages in the headquarters country. For time periods in which firms hire a new worker in their headquarters, we compute the average wage of these new domestic hires. Regressing log headquarters wages on the headquarters-country exchange rate, controlling for firm fixed effects, provides an estimated pass-through of 0.704. In other words, changes in the headquarters-country exchange rate translate into changes in headquarters wages measured in US dollars.

Column (2) uses the full sample of fixed contracts with foreign remote workers and estimates the

¹²As argued by Hjort et al. (2026b), headquarters wages measured in USD respond to exchange-rate movements if firms do not fully index local-currency wages to USD. Wages of international remote workers measured in USD will then move with headquarters wages if, for example, firms anchor these workers’ wages to headquarters wages, whether the anchor is expressed in the headquarters currency or in USD.

reduced form relationship between remote wages and exchange rates. Foreign remote wages respond to exchange rates in both the firm’s headquarters country and the worker’s country in the month the contract begins. The elasticity with respect to the headquarters-country exchange rate is 0.258, while the elasticity with respect to the worker-country exchange rate is 0.143. Thus, even conditional on exchange-rate movements in the worker’s own country, remote wages move with currency fluctuations at the firm’s headquarters.

Finally, Column (3) combines these two relationships into a two-sample two-stage least squares (TS2SLS) design ([Angrist and Krueger \(1992\)](#); [Inoue and Solon \(2010\)](#)), instrumenting headquarters wages with the headquarters-country exchange rate. This approach is useful because headquarters wages are observed only in months when the firm hires a new domestic worker, whereas the reduced form relationship can be estimated using the larger sample of international remote contracts. TS2SLS therefore uses all available firm-months with headquarters hires to estimate the first stage and all foreign remote contracts to estimate the reduced form. Standard errors are computed following [Pacini and Windmeijer \(2016\)](#).

The TS2SLS estimate implies that a 1% increase in the average wage paid at a firm’s headquarters raises the wage paid to its foreign remote workers in the same month by 0.37%. This magnitude of 0.37 is larger than the estimate for traditional multinational firms in [Hjort et al. \(2026b\)](#) of 0.14. Wage anchoring could be stronger in our setting because, without physical establishments separating workers into local units, workers across countries may interact more closely, creating greater pressure for firm-wide wage norms, as discussed in Section 3.

5 Firm Sorting and Cross-Country Differences in Remote Wages

The results thus far establish that firm fixed effects substantially mediate the relationship between local labor market conditions and remote wages. The impacts of exchange-rate shocks indicate that this firm component reflects, at least in part, firms’ wage-setting practices rather than solely differences in worker skills. While the preceding analysis examines how remote wages relate to workers’ local labor market conditions, we now turn to cross-country differences in remote wages themselves, investigating how large these differences are and what accounts for them, focusing on firm-specific wage premia.

We follow [Card et al. \(2016\)](#), who study the contribution of firm-specific wage premia to the gender pay gap. We decompose the role of firm pay premium into the *sorting channel*—whether workers from high-income countries are more likely to be employed at high-wage firms—and the *within-firm channel*—whether workers from high-income countries are paid more while employed in the same firm. The sorting of workers from different backgrounds across firms is likely indicative of human capital differences across workers, potential hiring discrimination, and various hiring frictions such as uncertainty about worker ability. On the other hand, pay differences within firms are likely indicative of how firms set wages across space, to what extent firms engage in firm-wide wage-setting, and

differences in worker bargaining power.

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 particular, we consider the wage gap between workers from high-income countries (country set $\mathcal{J}$) and workers from middle-income countries (country set $\mathcal{K}$), following the World Bank income classification.¹³

We then estimate the following model:

$$\log w_{it} = \delta_{f(i,t)}^{C(i)} + \beta^{C(i)} X_{it} + \epsilon_{it} \quad (3)$$

where $C(i) \in \{\mathcal{J}, \mathcal{K}\}$ is the country set for which worker i belongs. $\delta_{f(i,t)}^{C(i)}$ is a fixed effect for firm $f(i,t)$, for worker i at time t , while X_{it} includes various covariates for worker i at time t (occupation, contract type, contract start year and month, experience level, and pay frequency). All regressors—both the firm fixed effects and the covariates—are country set-specific. Moreover, following Card et al. (2016), we restrict the sample to firms that hire at least one worker from each country set, so that we can identify what firms would pay workers in each country set. This specification controls for observable worker characteristics and thus focuses on the contribution of firms to wage differences between workers from high-income countries and workers from middle-income countries.

We then decompose the overall contribution of firm pay premia towards the difference in wages into a within-firm channel and a sorting channel:

$$\begin{aligned} E[\delta_{f(i,t)}^{\mathcal{J}} | \text{country set } \mathcal{J}] - E[\delta_{f(i,t)}^{\mathcal{K}} | \text{country set } \mathcal{K}] &= \underbrace{E[\delta_{f(i,t)}^{\mathcal{J}} - \delta_{f(i,t)}^{\mathcal{K}} | \text{country set } \mathcal{J}]}_{\text{Within-firm channel}} \\ &\quad + \underbrace{E[\delta_{f(i,t)}^{\mathcal{K}} | \text{country set } \mathcal{J}] - E[\delta_{f(i,t)}^{\mathcal{K}} | \text{country set } \mathcal{K}]}_{\text{Sorting channel}} \end{aligned} \quad (4)$$

The overall contribution of firm pay premia can be decomposed in a parallel way:

$$\begin{aligned} E[\delta_{f(i,t)}^{\mathcal{J}} | \text{country set } \mathcal{J}] - E[\delta_{f(i,t)}^{\mathcal{K}} | \text{country set } \mathcal{K}] &= \underbrace{E[\delta_{f(i,t)}^{\mathcal{J}} - \delta_{f(i,t)}^{\mathcal{K}} | \text{country set } \mathcal{K}]}_{\text{Within-firm channel}} \\ &\quad + \underbrace{E[\delta_{f(i,t)}^{\mathcal{J}} | \text{country set } \mathcal{J}] - E[\delta_{f(i,t)}^{\mathcal{J}} | \text{country set } \mathcal{K}]}_{\text{Sorting channel}} \end{aligned} \quad (5)$$

¹³We drop workers in low-income countries, as these only account for a small percentage (0.3%) of workers. Middle income countries include workers from both upper middle-income (63.3%) and lower middle-income (36.7%) countries.

In the first decomposition (Equation (4)), 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 (5)) has an analogous interpretation, where the country sets are simply alternated. The wage premium for a given firm is identified in Equation (3) relative to a reference firm. In particular, the firm premia are normalized so that they are identified relative to a set of firms that provide no premium.¹⁴

One difference between this paper’s specification and that of Card et al. (2016) is that, because this paper’s data does not contain a sufficiently large number of workers switching firms, we cannot estimate worker fixed effects (Abowd et al. (1999)). As a result, we cannot control for unobserved baseline productivity differences across workers from different country groups beyond the observable characteristics already included in Equation (3). Consequently, the estimated firm pay premia, $\delta_{f(i,t)}^{C(i)}$, may partly reflect unobserved productivity differences among the workers employed by each firm. These differences are likely small, given that the observable worker characteristics already included in equation 3 are rich measures. Figure A2 shows that the estimated firm fixed effects in Equation (3) are very similar to the firm fixed effects estimated in a specification with worker fixed effects as well.

5.2 Empirical results

Table 4 reports the results. Column (1) shows that the wage gap between workers from high-income countries and workers from middle-income countries is 0.481 log points. Thus, despite the wage anchoring to the firm’s headquarters, large wage differences remain between workers around the world. Columns (2) and (3) show that most workers are found in firms that hire workers from both country sets. 87.8% and 77.1% of workers in high-income and middle-income countries are in the restricted sample of firms that hire workers from both sets of countries, respectively.

As shown in Column (4), the overall difference in firm premia is 0.350 log points, which is over half (73%) of the overall wage gap. We then decompose this share into the relative contribution of the sorting and within-firm channels. Columns (5) and (6) show that the sorting channel explains between 34% and 43% of the overall wage gap, depending on whether the firm effects for high-income countries or middle-income countries are used. Finally, Columns (7) and (8) show that the within-firm channel explains a smaller, but still significant, share—between 30% and 39%—of the wage difference, depending on which distribution of jobs is used.

¹⁴While the choice of normalization affects the within-firm channel estimates, the sorting channel is invariant to the chosen normalization. We follow Card et al. (2016) and normalize all firms in the lowest-paying industry (outsourcing) to have pay premium of zero.

Heterogeneity As shown in the middle and bottom parts of Table 4, the cross-country wage gap and relative contribution of firms varies by the skill level of the worker’s occupation and by the experience level of workers (both using the same categorization from Section 3), respectively. The wage gap is smallest, and firm pay premia play the largest role, for workers in higher-skilled occupations and more experienced workers, each consistent with the heterogeneity analysis in Section 3.

Mechanisms and discussion Overall, the sorting of workers from different countries into different firms explains a large share (over one-third) of cross-country wage differences. Workers from high-income countries are systematically hired by higher-paying firms, potentially reflecting differences in human capital (Martellini et al. (2024)), hiring discrimination and uncertainty about worker ability (Leung (2018); Pallais and Sands (2016)), 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 differences.

Figure 1 further explores the sorting channel by examining the relationship between worker human capital and firm pay premia. The discussion focuses on firm fixed effects estimated using workers from high-income countries, although the patterns are similar when using the firm fixed effects estimated from middle-income countries, as shown in the figure. Panel (a) shows that workers in higher-skilled occupations work for firms with average pay premia that are 0.23 log points greater than those in lower-skilled occupations. Panel (b) shows that workers in the most experienced category work for firms with average pay premia that are 0.16 log points greater than those of workers in the least experienced category. Finally, Panel (c) shows that workers from more educated countries are employed by higher-paying firms than are workers from less educated countries.

These findings provide evidence of positive sorting between workers’ human capital and the firms they end up in. They suggest that workers from high-income countries sort into higher-paying firms because, at least in part, they possess higher levels of human capital. For workers and governments hoping to benefit from the expanding labor market opportunities created by remote multinationals, these findings suggest that investments in human capital could help reduce disparities in firm sorting, an important contributor to cross-country wage differences in this labor market. At the same time, additional data are needed to further identify the economic mechanisms underlying the sorting of workers into firms and to better inform policy design.

6 Concluding Remarks

This paper uses a novel, large-scale data set on firms and their international remote workers to provide insights into wage-setting and firm sorting in cross-country remote hiring. Cross-country, remote hiring allows firms and workers to collaborate without having to physically migrate or establish a local

subsidiary, presenting opportunities for labor markets, trade, and development alike.

Wage differences across countries among workers employed by remote multinationals are substantially smaller than those observed among workers in the same occupations in their local labor markets. Moreover, within-firm wage differences are smaller than corresponding estimates in traditional multinational contexts. Using variation in exchange rates, we further show that this wage compression is at least partly causal: firms anchor the wages of their remote international workers to the wages they pay workers at headquarters.

At the same time, cross-country wage differences in remote wages do not disappear entirely. Differential sorting into firms—whereby workers from high-income countries are more likely to be employed by higher-paying firms—is a major contributor to remaining cross-country differences in remote wages and is likely partially related to differences in human capital. Further investigating wage determination and worker-firm matching in this growing mode of hiring is important for workers, firms, and policymakers around the world. More broadly, this paper suggests that international remote work can reduce the importance of geography in determining workers' labor market opportunities, but it does not eliminate it: while workers can increasingly access high-paying firms abroad without migrating, who gains access to those firms—and why—still varies dramatically.

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Tables and Figures

Table 1: Sample summary statistics

	Mean	SD	P25	P50	P75
<u>A. Contract-level</u> (N = 242,106)					
Contract length (realized, in months)	6.84	6.36	2	5	10
Start year	2022.35	0.69	2022	2022	2023
End year	2022.76	0.46	2023	2023	2023
Work contract completed	0.21	0.41			
Different country	0.92	0.69			
Different continent	0.63	0.46			
Hourly wage (USD)	24.17	21.86	5.91	16.52	35.51
<u>B. Worker-level</u> (N = 207,044)					
Nb. of work contracts	1.17	0.57	1	1	1
More than one work contract	0.12	0.33			
Work length (months)	7.89	7.32	2	6	13
Work contract completed	0.25	0.55			
Hourly wage (USD)	24.35	22.04	5.91	16.57	36.25
Nb. of workers in firm	243.29	594.30	12	39	128
Worked for multiple firms	0.03	0.18			
<u>C. Firm-level</u> (N = 22,629)					
Nb. of workers	10.70	52.40	1	2	8
Nb. of workers in different country	9.79	50.78	1	2	7
Nb. of workers in different continent	6.73	38.82	0	1	4
Nb. of unique worker countries	2.91	4.03	1	1	3
Nb. of unique worker occupations	2.21	2.03	1	1	3
Nb. of unique worker country-occ. combinations	4.09	6.90	1	2	4

Notes: This table reports summary statistics at the contract-, worker-, and firm-levels. The occupation classification includes 88 occupations overall. See Appendix C.1 for discussion of the wage variable and other data construction.

Table 2: Elasticity of remote wages to wages in local labor markets

	Hourly wage (log)						
				By Occ. Skill Level			
				Below-Median		Above-Median	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
log(worker country median wage)	0.414*** (0.006)	0.374*** (0.005)	0.189*** (0.005)	0.505*** (0.012)	0.423*** (0.015)	0.302*** (0.006)	0.138*** (0.006)
log(firm country median wage)	0.371*** (0.010)	0.337*** (0.009)	0.468*** (0.013)	-0.279*** (0.038)	-0.282*** (0.056)	0.205*** (0.011)	0.399*** (0.039)
Observations	30,684	30,684	30,684	3,880	3,446	26,796	26,643
Controls		Y	Y	Y	Y	Y	Y
Firm FE			Y		Y		Y

Notes: This table estimates Equation (1) and shows the relationship between the wages of remote workers and the median wage levels in their occupation in the worker's country and the firm's country. The sample is limited to fixed contract workers. Worker (firm) country median wage refers to median wages in the same occupation collected by Glassdoor in the worker's (firm's) country. Controls include fixed effects for worker experience level, start month and year of contract, and contract pay frequency. Occupational skill levels are defined in terms of above or below the average wage level in the worker's occupation. Standard errors are shown in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table 3: Anchoring of remote wages to headquarters wages

	log(HQ Wage)	log(Remote Wage)		
	FS	RF	TS2SLS	OLS
	(1)	(2)	(3)	(4)
log(HQ Exchange Rate)	-0.704*** (0.270)	-0.258*** (0.097)		
log(Worker Country Exchange Rate)		-0.143*** (0.019)	-0.143*** (0.019)	-0.157 (0.121)
log(HQ Wage)			0.366* (0.196)	0.085*** (0.012)
Observations	3,713	117,146	117,146	7,647
Worker Country $\times$ Year FE		Y	Y	Y
Firm FE	Y	Y	Y	Y

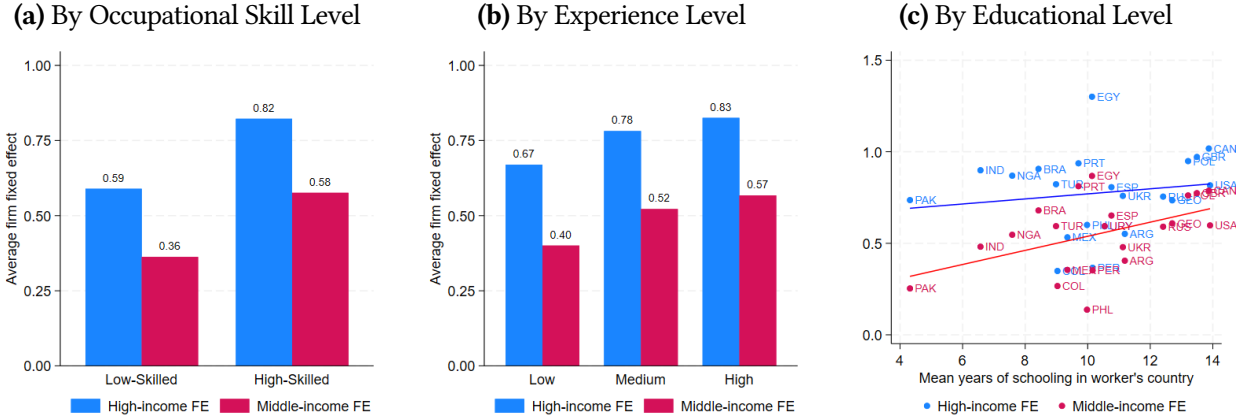
Notes: This table presents estimates of the pass-through of firm headquarters wages to the wages of internationally hired remote workers, using exchange rate shocks as a source of identifying variation and as described in Equation (2). Each observation is a new contract and the sample is limited to fixed contracts. Column (1) reports the relationship between the average wage paid to a firm's domestic headquarters workers newly hired in a given month and the same headquarters-country exchange rate; this column only includes firm-months in which we observe a new headquarters hire. Column (2) reports the relationship between the wage of remote workers hired in a given month and the exchange rate of the firm's headquarters country in the same month (local currency units per USD). Column (3) reports estimates from a two-sample 2SLS regression in which we instrument for the headquarters wage using the exchange rate. The first stage includes all firm-months with a new headquarters hire, even if there is no new foreign remote hire that month; the second stage includes all foreign remote hires, even if there is no new headquarters hire at the firm that month. All columns include firm fixed effects. Columns (2), (3), and (4) additionally control for the monthly exchange rate of the worker's country's currency to USD and include worker country $\times$ year fixed effects. All standard errors are clustered at the firm's headquarter country's currency zone level. TS2SLS standard errors are computed following [Pacini and Windmeijer \(2016\)](#). *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table 4: Contribution of firm pay premium to cross-country wage differences

	Sample sizes				Decomposition of Firm Component Difference			
	Overall wage gap	High-income	Middle-income	Total contribution of firm components	Sorting		Within-firm	
					Using high-income effects	Using Middle-income effects	Using high-income distribution	Using Middle-income distribution
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
All	0.481	11049 (87.83)	36509 (77.14)	0.350 (72.75)	0.145 (42.52)	0.186 (34.12)	0.204 (30.23)	0.164 (38.63)
By skill level:								
Below-median	0.746	2896 (89.16)	8707 (73.83)	0.352 (47.22)	0.111 (32.37)	0.178 (23.40)	0.241 (14.86)	0.175 (23.82)
Above-median	0.439	8153 (87.35)	27802 (78.18)	0.361 (82.16)	0.158 (46.17)	0.188 (39.28)	0.203 (35.99)	0.172 (42.89)
By experience level:								
Low	0.603	862 (84.80)	3300 (66.18)	0.306 (50.67)	0.073 (38.56)	0.196 (18.19)	0.233 (12.11)	0.110 (32.48)
Middle	0.475	1742 (87.77)	6885 (73.61)	0.306 (64.38)	0.152 (32.44)	0.182 (26.03)	0.154 (31.94)	0.124 (38.35)
High	0.334	3105 (82.74)	7464 (73.23)	0.354 (105.97)	0.196 (47.38)	0.190 (49.13)	0.158 (58.59)	0.164 (56.84)

Notes: The wage gaps shown are between two country sets: high-income countries and middle-income countries. The sample is again limited to fixed contract workers. The sample size refers to the sizes of connected sets, with the share of the overall sample in parentheses underneath. The parentheses in columns (5) through (9) refer to the share of the overall wage gap explained by the sorting or within-firm channel, as indicated. The below-median skill level is defined as an occupation with occupation-specific mean wage below the median and the above-median skill level is defined analogously. The low experience level is defined as having the experience variable equal to junior, middle experience is defined as having experience equal to mid, and high experience is defined as having experience equal to senior or above.

Figure 1: Firm pay premium by different measures of worker human capital



Notes: This figure shows average firm pay premia by worker characteristics. Firm pay premia are estimated via Equation (3). This figure uses firm pay premia for high-income countries and middle-income countries separately, as indicated. Panel (a) considers two levels of occupational skill and Panel (b) considers three levels of worker experience, using the same classification as in Table 4. Panel (c) considers the average years of schooling in the worker's country.

Online Appendix

“Remote Multinationals: Wage Compression and Worker Sorting in Cross-Country Remote Work”

Jingyi Cui and Samuel M. Solomon

A Appendix Tables

Table A1: Wage variance decomposition

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

Notes: This table provides a variance decomposition of wages. Each column progressively adds covariates. The third column includes the country of the worker, the firm, and the worker's occupation. Other controls include the contract type, contract start year and month, experience level, and pay frequency.

Table A2: Elasticity of remote wages to wages in local labor markets: using GDP per capita

	Hourly wage (log)						
				By Occ. Skill Level			
				Below-Median		Above-Median	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
log(worker country GDP per capita)	0.301*** (0.002)	0.271*** (0.002)	0.148*** (0.002)	0.341*** (0.003)	0.202*** (0.003)	0.202*** (0.003)	0.100*** (0.003)
log(firm country GDP per capita)	0.159*** (0.004)	0.161*** (0.004)		0.075*** (0.005)		0.235*** (0.005)	
Observations	122,863	122,863	122,863	69,625	68,465	53,234	52,165
Controls		Y	Y	Y	Y	Y	Y
Firm FE			Y		Y		Y

Notes: This table estimates Equation (1), but with the GDP per capita in the worker's and firm's countries instead of the median wage levels in their occupation. The sample is limited to fixed contract workers. Controls include fixed effects for worker experience level, start month and year of contract, and contract pay frequency. Occupational skill levels are defined in terms of above or below the average wage level in the worker's occupation. Standard errors are shown in parentheses.

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table A3: Elasticity of remote wages to wages in local labor markets: using GDP per capita (all workers)

	Hourly wage (log)						
				By Occ. Skill Level			
				Below-Median		Above-Median	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
log(worker country GDP per capita)	0.462*** (0.002)	0.418*** (0.002)	0.262*** (0.002)	0.477*** (0.002)	0.303*** (0.002)	0.318*** (0.002)	0.199*** (0.002)
log(firm country GDP per capita)	0.159*** (0.004)	0.167*** (0.003)		0.119*** (0.004)		0.209*** (0.005)	
Observations	218,404	218,404	218,404	132,561	130,713	85,842	83,906
Controls		Y	Y	Y	Y	Y	Y
Firm FE			Y		Y		Y

Notes: This table estimates Equation (1), but with the GDP per capita in the worker's and firm's countries instead of the median wage levels in their occupation. The sample is not limited to fixed contract workers and instead includes all workers. Controls include fixed effects for worker experience level, start month and year of contract, contract pay frequency, and contract type. Occupational skill levels are defined in terms of above or below the average wage level in the worker's occupation. Standard errors are shown in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table A4: Elasticity of remote wages to wages in local labor markets: using GDP per capita (Glassdoor sample)

	Hourly wage (log)						
				By Occ. Skill Level			
				Below-Median		Above-Median	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
log(worker country GDP per capita)	0.278*** (0.005)	0.258*** (0.004)	0.128*** (0.004)	0.406*** (0.009)	0.326*** (0.011)	0.217*** (0.005)	0.101*** (0.004)
log(firm country GDP per capita)	0.168*** (0.013)	0.186*** (0.012)		0.267*** (0.053)		0.195*** (0.011)	
Observations	30,353	30,353	30,353	3,864	3,434	26,482	26,332
Controls		Y	Y	Y	Y	Y	Y
Firm FE			Y		Y		Y

Notes: This table estimates Equation (1), but with the GDP per capita in the worker's and firm's countries instead of the median wage levels in their occupation. The sample is limited to fixed contract workers and workers for which corresponding wage data from Glassdoor exists. Controls include fixed effects for worker experience level, start month and year of contract, and contract pay frequency. Occupational skill levels are defined in terms of above or below the average wage level in the worker's occupation. Standard errors are shown in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

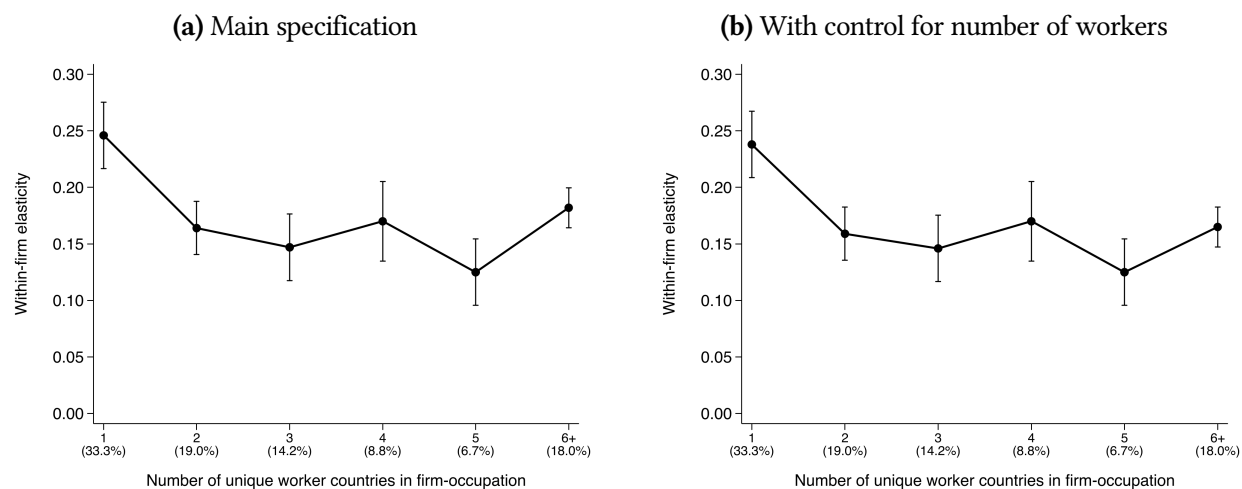
Table A5: Elasticity of remote wages to wages in local labor markets: by worker experience

	Hourly wage (log)					
	By Experience Level					
	Low		Middle		High	
	(1)	(2)	(3)	(4)	(5)	(6)
log(worker country median wage)	0.394*** (0.016)	0.148*** (0.021)	0.326*** (0.012)	0.179*** (0.013)	0.295*** (0.009)	0.131*** (0.010)
log(firm country median wage)	0.102*** (0.028)	0.262*** (0.047)	0.292*** (0.020)	0.323*** (0.033)	0.212*** (0.015)	0.257*** (0.029)
Observations	2,928	2,429	5,951	5,259	8,338	7,616
Controls	Y	Y	Y	Y	Y	Y
Firm FE		Y		Y		Y

Notes: This table estimates Equation (1) and shows the relationship between the wages of remote workers and the median wage levels in their occupation in the worker's country and the firm's country. The sample is limited to fixed contract workers. Worker (firm) country median wage refers to median wages in the same occupation collected by Glassdoor in the worker's (firm's) country. Controls include fixed effects for worker experience level, start month and year of contract, and contract pay frequency. The sample is split by the worker's experience level. The low experience level is defined as having the experience variable equal to junior, middle experience as having experience equal to mid, and high experience as having experience equal to senior or above. Standard errors are shown in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

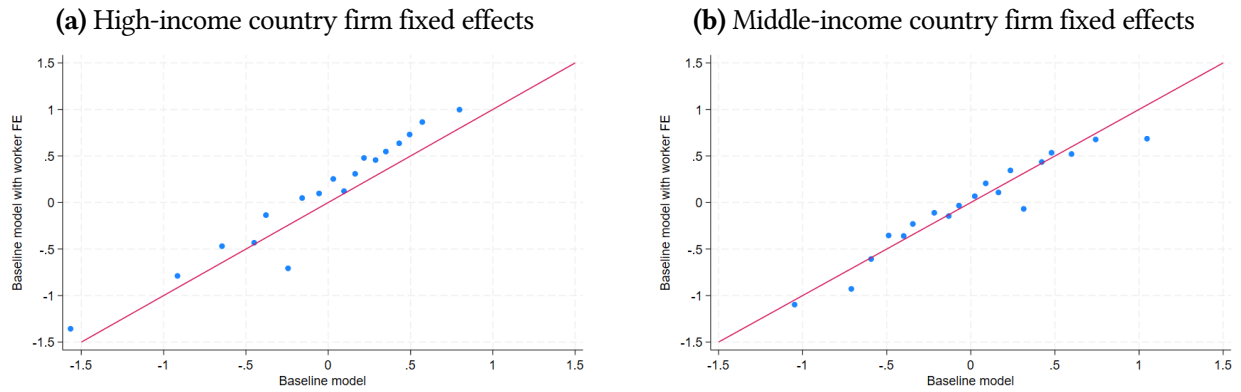
B Appendix Figures

Figure A1: Within-firm elasticity of remote wages to wages in local labor markets: by firm composition



Notes: This figure provides estimates of Equation (1) including firm fixed effects. The sample is split by the number of unique worker countries in the same occupation in the worker's firm. The percentages on the horizontal axis indicate the share of the sample in each group. Panel (a) uses the main specification while Panel (b) includes a control for the number of workers in the occupation in the worker's firm.

Figure A2: Robustness of firm fixed effects to including worker fixed effects



Notes: This figure plots a bin scatter relating the firm fixed effects estimated in Equation (3) with the firm fixed effects estimated in Equation (3) with worker fixed effects. The 45-degree line is also shown. Panel (a) considers the high-income country firm fixed effects and Panel (b) considers the middle-income country firm fixed effects. The slope in Panel (a) is 1.075 (0.017), while the slope in Panel (b) is 0.919 (0.009).

C Data Appendix

C.1 Variable construction

The data from Deel contains the following variables, from which we derive the 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.
2. Total earnings: This is simply given by `sum_amount_invoiced`.

Using the procedure above allows us 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.

The other main variables in the data include:

1. Job titles and occupations: We condense over 44,000 unique job titles into 96 unique occupations, manually classifying 60.3% of job titles.
2. Worker experience level: The worker experience variable is classified into 10 groups. These groups include “junior”, “mid”, “senior”, ..., “senior vice president”, “C-level executive”. We classify low experience as “junior”, medium experience as “mid”, and high experience as “senior” and above.

C.2 Sample restrictions

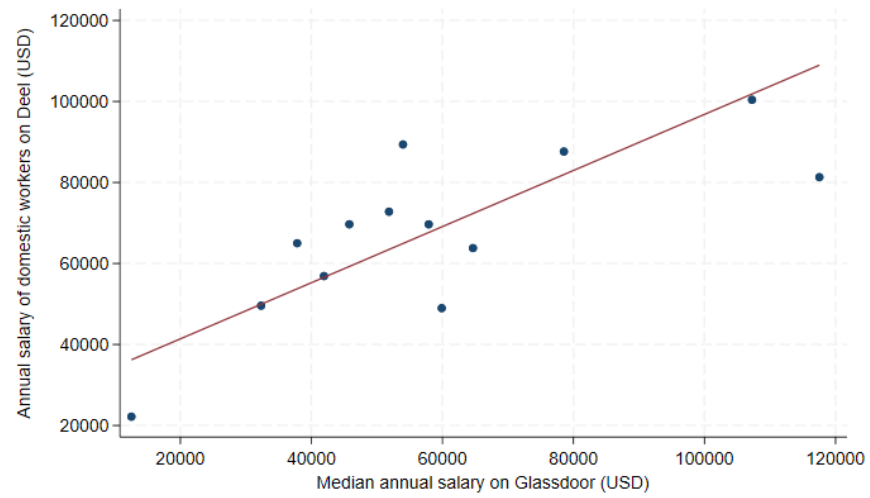
We make the following sample restrictions to the data. First, we limit the sample to work relationships that have positive income to ensure that we only consider relationships for which work actually occurred. Second, we limit the data to firms that have one location used. This restriction is made so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

C.3 Validation of wage data

To investigate the quality of the Deel and Glassdoor data, we take advantage of the subsample 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 issue, it is still informative to see if the wages of the subsample approximate wages from the Glassdoor data.

We conduct two exercises to compare wages of domestic hires in the Deel data 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, which is 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 A3, the coefficient is 0.69 and is statistically significant. The fact that the coefficient is relatively close to 1 provides further assurance of the validity of Deel's data and the use of the Glassdoor data to proxy for the outside options of workers.

Figure A3: Domestic wages on Deel vs. domestic wages on Glassdoor



Notes: This figure shows a binned scatterplot of Deel wages against Glassdoor wages for the same country-occupation pairs. Each point represents one or more country-occupation pairs. The estimated slope is 0.69 (0.02).