The Impacts of Global Remote Work on the Careers of Workers

Eric Solomon[*] Samuel M. Solomon[†]

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[This draft is preliminary and incomplete. Please do not circulate.]

Abstract

Global remote hiring has increased dramatically in recent years and now rivals prominent visa programs in scale. By connecting firms and workers across cities and countries, global remote work has the potential to provide opportunities to workers regardless of their location. We compare workers that transition into a global remote firm with comparable workers that transition into traditional non-remote firms and estimate differences-in-differences models to identify the impact of switching into a global remote firm in particular. Access to global remote firms increases income for workers, both domestic and foreign, and is largely driven by access to higher-paying firms overall. Access to global firms also improves workers' peer composition, as measured by the share of coworkers with a college degree. These impacts persist even after workers further transition into a new firm, suggesting that workers experience permanent increases in human capital. Workers also move up the job ladder more quickly after entering a global remote firm. Finally, access to global firms increases the likelihood that workers become innovators and enter executive positions.

JEL Codes: J21, J61, F66, O15.

Keywords: Remote work; labor market; global hiring; immigration; innovation.

[*]Yale University

[†]Temple University

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1 Introduction

Remote work has grown significantly in recent years around the world, due to advances in technology and the Covid-19 pandemic (Aksoy et al. (2025); Barrero et al. (2023a)). Furthermore, as economies have grown, an increasing number of jobs can be conducted from anywhere; over one-third of jobs in the United States can be done remotely, and these jobs disproportionately represent higher-paying occupations (Dingel and Neiman (2020)). By removing geographical constraints, remote work has the ability to provide new workers with new opportunities, independent of location. These geographic constraints span both domestic and international locations, potentially creating large scope for gains from trade for workers and firms.

This paper studies the impacts of global remote work on workers' labor market outcomes and career trajectories. We focus on the impact of remote work for workers, investigating how access to new remote jobs discretely changes their labor market experiences. To measure the impact of remote work on workers from around the world, we use data on workers' LinkedIn profiles provided by Revelio Labs. In essence, this data has the same flavor as a global matched employee-employer data set, which to our knowledge does not exist in the same breadth and depth anywhere else. To identify firms that offer global remote work, we consider firms that have utilized global human resources firms that facilitate cross-country hiring. There has been a rapid growth of these global HR firms, such as Deel and Rippling, which are meeting their clients' growing demands to hire remotely.

The sampling procedure leads to a sample of over 300 firms, covering over 200,000 workers that represent over 200 countries and a broad array of occupations. We estimate how the career trajectories of workers that are hired remotely by one of these firms changes, relative to an observably-similar worker that switches into a traditional, non-remote firm. In particular, for each worker we identify a comparable control worker, who has the same demographic and occupational characteristics at the time of the job switch. We then estimate differences-in-differences models, which include worker fixed effects to absorb any additional baseline differences in worker productivity, in addition to other regression controls. This specification yields an estimate of the impact of switching into a global remote firm above and beyond the impact of an average job transition.

The first main result of this paper is that access to global remote work increases both job retention and imputed measures of income for workers. Workers do not exhibit significant pretrends, implying that workers that enter a global remote firm were on a similar career trajectory as workers that enter a traditional firm. Workers that enter a global remote firm receive a 4.4% wage increase relative to similar workers that make a job transition into a traditional firm. This increase is driven by an increase in access to higher-paying firms, which is consistent with substantial

firm-wide wage-setting in this market, as found in Cui and Solomon (2025).

Furthermore, workers—through gaining access to higher-paying firms—also gain access to firms with a significantly different coworker composition. While gaining access to these firms increases the share of coworkers that are foreign by 51%, it also increases the average education of one's coworkers: it increases the share of coworkers that have a college degree by 11% and improves the average ranking of the university that coworkers attended by 22 ranks. These gains are experienced for both domestic workers (i.e., workers located in the same country as the firm) and foreign workers.

The second main finding of this paper is that these impacts on workers do not disappear once workers leave their new firm—which we also refer to as their target firm—and instead result in sustained improvements in human capital and career trajectories. Among all workers that have left their target firm, treated workers still earn 1.7% more relative to comparable workers, which is again partially due to access to higher-paying firms. In the initial job transition, entering a global remote firm increases the likelihood of working for a foreign firm by 20 percentage points, or 58% relative to the pre-event control mean. In the two years following the job transition, workers that have left their initial firm are still 2 percentage points, or 6%, more likely to be working for a foreign firm. They are also more likely to be working for a firm with a greater share of foreign workers and college-educated workers, suggesting that global remote work permanently affects the type of firms and jobs a worker enters later in their career.

In addition to sustained impacts on workers when they leave their target firms, global remote work also impacts workers' abilities to climb occupational ladders. Workers are more likely to switch occupations within their target firm, and enter occupations that are more substantively different than their initial occupation. Finally, access to global remote work impacts both workers' ability to become innovators as well as enter executive positions. Entering a global remote firm increases the share of one's coworkers that have been a founder in the past, and ultimately affects the worker's own propensity to become a founder, by 57%. Similarly, entering a global remote firm increases the likelihood that a worker will hold an executive position in the following two years by 80%.

Relation to the literature This paper contributes to the recent, growing literature on remote work by identifying the impacts of access to a pool of global firms on workers' careers. There are now several studies that have documented how remote work has accelerated in recent years and especially since the Covid-19 pandemic (e.g., Barrero et al. (2023a)), and its implications for productivity (Bloom et al. (2025); Emanuel and Harrington (2024)) and on-the-job learning (Emanuel

et al. (2023), among many other topics.[1] Cui and Solomon (2025) and Brinatti et al. (2021) have studied wage-setting in the context of global, white collar work.[2] Our paper contributes to these studies by estimating the within-worker impacts of gaining access to remote work, which we find to be large and significant. To estimate the within-worker impacts requires information on workers' careers before and after the job changes, which the LinkedIn data facilitates in ways which is otherwise difficult to find.

In addition to the remote work literature, this paper contributes to the immigration literature, by identifying another means by which workers from around the world can access new firms and jobs. In this paper's case of global remote work, workers access foreign firms that they in prior years would have had to physically immigrate to other countries to access. A large literature has measured the impacts of traditional immigration on workers, including among more educated workers and those on H-1B visas in the United States for example (e.g., Amanzadeh et al. (2024); Doran et al. (2022); Amuedo Dorantes et al. (2023); Dustmann et al. (2016); Kerr et al. (2015); Mahajan (2024); Mahajan et al. (2024)).

Particularly close to our work is Clemens (2013), which estimates the increase in wages from a lottery for a computer programmer to work in the United States compared to India, within the same firm and project team. Clemens (2013) finds that location alone increases wages by five to six times in the United States compared to in India. Clemens et al. (2019) similarly estimate wage differences for workers among 42 different developing countries compared to similar workers in the United States, and finds that workers experience a significant wage premium for working for an American firm. We contribute to this line of research by showing that providing access to remote jobs, which do not require physical relocation, can provide similar opportunities for workers regardless of home location.

Paper outline The remainder of this paper proceeds as follows. Section 2 further discusses the context of global remote work and the data, while Section 3 describes the empirical strategy. Section 4 shows the impacts of global remote work on workers and Section 5 focuses on impacts on downstream career success. Lastly, Section 6 concludes.

[1] Other work regarding remote work and the effects of the Covid-19 pandemic includes, but is not limited to, the implications for labor force participation (Barrero et al. (2023b)), cities (Ramani et al. (2024); Yoo (2024)), gender wage differences (Harrington and Kahn (2025)), housing (Mondragon and Wieland (2022), and individual time use (Aksoy et al. (2023)).

[2] Hjort et al. (2020) studies wage-setting in the similar context of multinationals across countries. Hazell et al. (2022) also studies firm-wide wage-setting, although in a domestic context (within the United States). Other similar settings include Drenik et al. (2023); Minni (2024).

2 Context and Data

2.1 Context

This paper considers the global remote labor market for white collar work. In particular, the paper focuses on firms that hire workers remotely across geographic boundaries (across both countries and across localities within countries). Various human resources companies have formed to help facilitate such cross-border hiring. The size of this market is not precisely known, but recent estimates suggest it has surpassed one million workers in 2023 (Dahan (2024)). The latest projection from Deel, one of the leading global HR firms, is that they facilitate 22 billion USD in annual payroll, supporting 1.5 million workers around the world (Thompsett (2025)).[3] For comparison, there are currently about 400,000 workers on H-1B visas in the United States, with a median salary of $120,000 (USCIS (2025)). Overall, these statistics suggest that this new mode of hiring is economically meaningful.

2.2 Data

2.2.1 Firm sampling frame

We use data on firms that are publicly known to have adopted a global human resources (HR) firm to facilitate their global hiring and payroll. In particular, we scrape public case studies from global HR firms of their clients from the various HR firms' websites. We consider the following five HR firms: Deel, Oyster, Papaya, Remote, and Rippling. For each firm, we look at the case studies of their clients and use those clients as our sampling frame of firms. Figures A1 and A2 show examples of clients for which Deel and Rippling have helped facilitate global hiring.

2.2.2 LinkedIn data

We also use data from LinkedIn, as provided by Revelio Labs, to track the workers in the adopting firms as well as on various firm dynamics. These data contain the self-reported educational and labor market histories of individuals for over one billion users around the world (LinkedIn (2026)).[4] We focus on the educational background of workers, their employment and career trajectories, their imputed earnings, and their coworker composition. We then compute monthly aggregate firm-level characteristics from the set of workers at each firm in each month. This

[3] Cui and Solomon (2025) study a subset of work contracts processed on Deel, where the average remuneration was $34,000 per year.

[4] It is important to note that LinkedIn profiles represent a selected sample of workers across the globe, and tend to overrepresent younger workers in professional occupations. Still, prior work has shown that, in the United States, these data are fairly representative (Tambe (2026)).

enables us to observe each firm's composition of workers, growth and expansion over time, and total wage bill. Appendix C.1 further describes the firm sampling frame we use and provides simple validation checks that suggest the LinkedIn data captures well the workers for a given firm. Appendix C.2 discusses the Revelio Labs data further.

2.2.3 Supplementary data

O*NET In order to characterize the occupational trajectories of workers, we assign a Standard Occupational Classification (SOC) code to each position. These codes are from the Occupational Information Network (O*NET), a comprehensive database maintained by the U.S. Department of Labor. The O*NET data contain vast descriptions of occupations, including abilities, job skills, and required knowledge. Appendix C.3 further discusses how we assign a SOC code to each position listed on LinkedIn.

2.3 Summary statistics

The main estimation sample is composed of all workers that enter a global remote firm starting in 2016, with a few exceptions. We drop from the estimation sample workers that found the target firm they join, which is less than 1% of the sample. Moreover, we focus on workers that are transitioning from previous employment, which is 75% of the sample (6% enter the new job after education while 19% enter the new job from a period of unemployment).

Table 1 shows summary statistics at both the worker-level and firm-level. The average worker is 27 when they transition into one of the remote firms, 67% of workers are male, and 55% of workers list a college degree. The median imputed salary is $61,023. 33% of workers are located in the same country as their firm's headquarters. As shown in Columns (2) and (3), domestic workers tend to be older and earn more than foreign workers. The average remote firm has a size of 560 workers and represents workers from 11 unique countries. Figure A3 shows that the firms represent a variety of industries, with the top five industries being professional services, manufacturing, information, finance and insurance, and educational services.

Figure 1 shows where workers and firms are located. Firms tend to be located in higher-income countries: 56% of firms are in the United States, 12% are in the United Kingdom, 4% are in Hong Kong, and 4% are in Canada. On the other hand, workers are more evenly distributed throughout countries. While some workers are in high-income countries (26% in the U.S., 11% in the U.K., and 8% in Israel), many workers are also in lower-income countries (22% in India, 4% in Brazil, and 2% in the Philippines).[5]

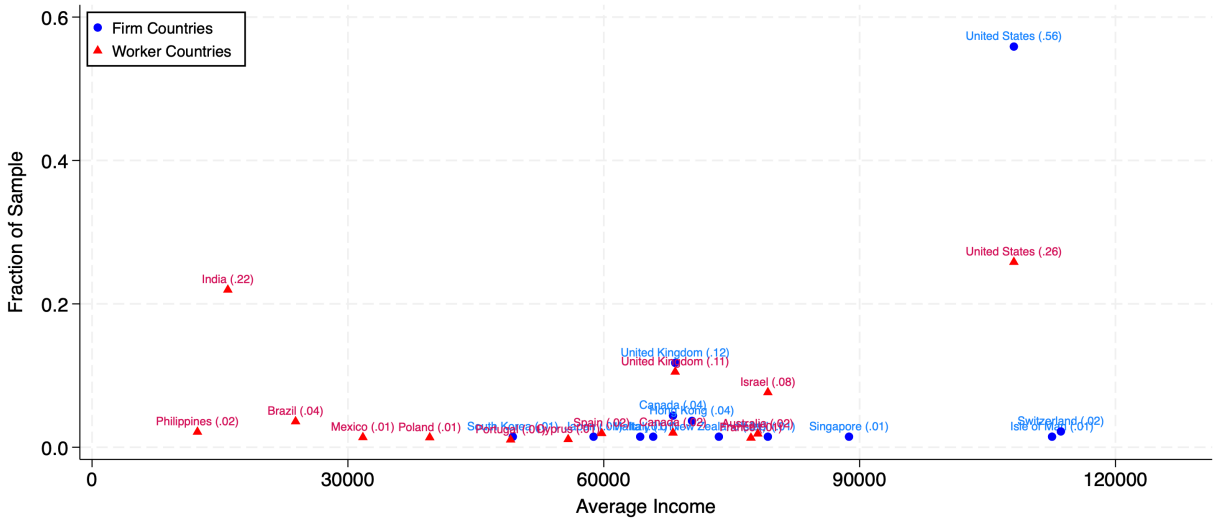
[5]Figure A4 shows that there are similar patterns within the United States. Firms tend to be located in higher-income states, while workers are more evenly distributed throughout the country.

Table 1: Sample Summary Statistics

	Overall (1)	Domestic (2)	Foreign (3)
Panel A: Worker-Level			
Age	27.09	28.80	26.32
Male	0.67	0.63	0.69
Salary	61023	98610	43134
Same Country	0.33	1.00	0.00
Has Bachelor	0.55	0.56	0.55
Has Graduate	0.21	0.20	0.22
Number of Observations	210135	66251	132522
Panel B: Firm-Level			
Number of Workers	560.4		
Total Worker Countries	11.3		
Number of Observations	375		

Notes: The table shows summary statistics at both the worker-level and the firm-level. Summary statistics are sample means. Worker-level summary statistics are shown for all workers, and then separately for domestic and foreign workers.

Figure 1: Worker and Firm Locations



Notes: This figure shows the distribution of worker locations and firm locations by country. Countries are sorted by their average worker salary. Blue dots show locations of firm countries and red dots show locations of worker countries. Only countries with greater than 1% in either category are shown. The firm distribution is not weighted by firm size.

3 Empirical Strategy

This section discusses how we estimate the impacts of joining a global remote firm on workers. In short, we compare outcomes before and after they join the firm. Since job-switching typically leads to changes in income and potentially other labor market outcomes such as job positions and firm-wide non-wage amenities (e.g., Sorkin (2018); Topel and Ward (1992)), we compare workers that switch into a global remote firm versus workers that switch into a traditional firm. This allows us to identify the effect of joining a *global remote* firm in particular.

To estimate the effect of entering a new remote job, compared to just a new job, we match workers with observably-similar characteristics. Specifically, for each worker in the sample we locate one control worker that also finds a new job and has the same worker country, gender, age at job switch, education, and occupation. We are able to match 89% of workers with a control worker. Appendix D further discusses the matching procedure.

We estimate the following differences-in-differences regression equation:

$$\begin{aligned} y_{it} = \beta_0 + \beta_1 \times [\text{Post}_{it}] + \beta_2 \times [\text{Post}_{it}] \times [\text{Global}_i] \\ + \beta_3 X_{it} + \gamma_i + \gamma_t + \gamma_o + \varepsilon_{it} \end{aligned} \tag{1}$$

for each worker i in month t, with treatment status $j \in \{\text{treatment, control}\}$. Post_{it} is an indicator for whether the worker has switched jobs and Global_i is an indicator for whether the new job for worker i is in a global firm or not. In addition to including worker time-varying controls X_{it} (age and education), we also include worker fixed effects (γ_i) to control for permanent worker differences. Finally, γ_t is a fixed effect for month t and γ_o is a fixed effect for the worker's current country o.

We consider primary outcomes of interest y_{it} at both the worker-level and the firm-level. At the worker-level, we consider job retention (whether the worker is at their new firm), whether the worker works for a foreign firm, their employment status, and their imputed income. At the firm-level, we consider the firm size, the average income of their firm, the share of workers that are not in the same country as the firm's headquarters, and various measures of coworker quality (including average education and global ranking of the universities they attend). For the firm-level outcomes, we use leave-one-out means rather than overall firm-wide means.

In the main specification given by Equation (1), β_1 represents the impact of switching jobs for the post-job switch period relative to the pre-job switch period for all workers. β_2 represents the additional impact of switching into a global firm for the post-job switch period relative to the pre-job switch period.

We also consider a dynamic version of Equation (1), where the treatment effects are allowed to vary around the job change. In particular, we estimate the following regression equation around

the event of joining a new firm ($\tau = 0$):

$$y_{it} = \beta_0 + \sum_{\tau=-M}^{N} \beta_{1\tau} \times [\mathbb{1}(\tau = t)] + \sum_{\tau=-M}^{N} \beta_{2\tau} \times [\mathbb{1}(\tau = t)] \times \text{Global}_{i,t+s} + \beta_3 X_{it} + \gamma_i + \gamma_t + \gamma_o + \varepsilon_{it} \tag{2}$$

for each worker i in month t with treatment status $j \in \{\text{treatment, control}\}$, as before, and with the same controls as before. In this specification, the coefficient $\beta_{1\tau}$ describes how outcomes change after workers switch into a new firm, for each time period τ. Our main coefficient of interest is $\beta_{2\tau}$, which describes how outcomes further change after workers switch into a new firm that is global and remote for each time period τ. All estimates are relative to the month before the job transition.

For both the static and dynamic specifications, we consider the 24 months before the job change and the 24 months after the job change as the main estimation window, and we then conduct estimation at the monthly level. In the main specification, we only consider workers that have a matched pair in the matching procedure, that have data for the entire estimation sample, and workers regardless of whether they stay at the target firm they switch into or subsequently leave, although we consider robustness to each of these restrictions.

4 Impacts of Global Remote Work on Workers

4.1 Main impacts

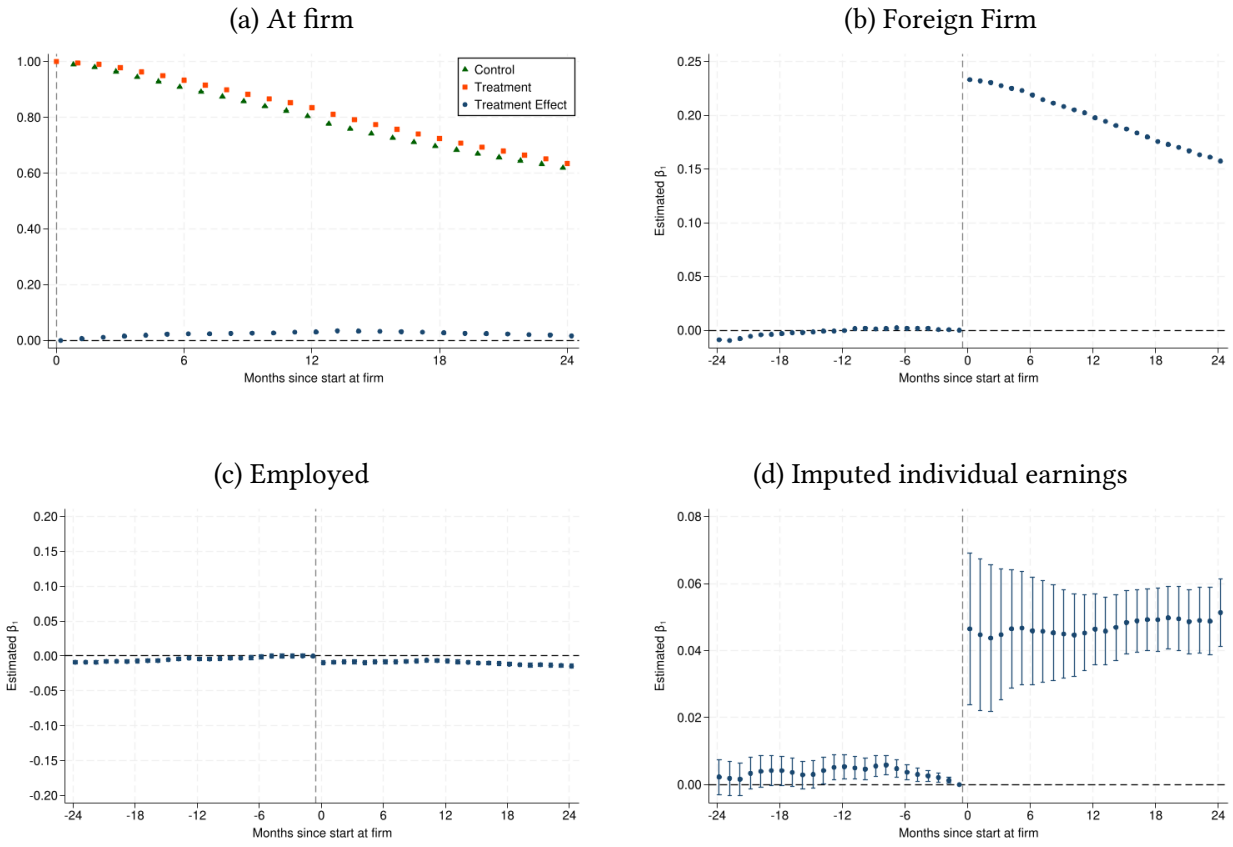
This section discusses the impacts of joining a global remote firm on workers. Figure 2 shows estimates of the main empirical specification, given by Equation (2), for various worker-level outcomes, while Table 2 shows point estimates of Equation (1) with underlying group means. We start by considering whether the individual remains at their target firm. Panel (a) of Figure 2 shows that 63% of treated workers are still at their target firm two years after making the job transition, which is greater than the share of control workers that stay at their target firm (61%), implying that the treatment increases retention by 2 percentage points in the long run.

As shown in Panels (b) through (d), there are no significant pre-trends in terms of whether the worker works for a foreign firm, worker employment status, or individual earnings.[6] Column (2) of Panel (A) of Table 2 shows that workers are 19.9 percentage points more likely to work for a foreign firm after entering a global remote firm, an increase of 58% relative to the pre-event

[6]Given that the LinkedIn data is survey data, it is possible that some workers fail to report employment for certain time periods on their profile. The lack of significant pre-trends in employment implies that this concern is minimal. Nevertheless, there are slight pre-trends in terms of employment.

control mean.[7] Column (3) shows that entering a global remote firm slightly reduces employment, although the magnitude is small. The remaining outcomes are conditional on employment, when applicable.

Figure 2: Dynamic Treatment Effects on Workers



Notes: This figure show estimates of Equation (2) for various outcomes. For Panel (a), the green refers to the control group (matched sample), the orange refers to the main treatment sample, and the blue is the difference, which is the main treatment effect of interest. Panel (a) does not include estimates before the job transition, as we are only concerned with retention at the new job. For all remaining panels, only the treatment effect is shown. Standard errors are clustered at the firm-level. 95% confidence intervals are shown.

As shown in Column (4), job transitions in general increase income by 7.6%. Job transitions into a global remote firm in particular further increase income by 4.4%. Column (2) of Panel (B) shows that this gain in income is largely driven by access to higher-paying firms overall. Workers that switch into a global remote firm, compared to a traditional firm, gain access to a firm that

[7]The percentage estimate is calculated by dividing the percentage point treatment effect (the coefficient on $\text{Post}_{it} \times \text{Global}_i$) by the pre-event control mean. This applies to other outcome variables as well.

Table 2: Impacts of Entering a Global Remote Firm on Workers

	(1)	(2)	(3)	(4)
Panel A: Worker-Level Outcomes				
	At Firm	Foreign Firm	Employed	log(Salary)
Post_{it}	0.824***	0.030***	0.000	0.076***
	(0.000)	(0.008)	(0.000)	(0.004)
$\text{Post}_{it} \times \text{Global}_i$	0.026***	0.199***	-0.005***	0.044***
	(0.000)	(0.046)	(0.000)	(0.006)
Treatment coef.	0.850	0.229	-0.005	0.120
Treatment S.E.	0.000	0.049	0.000	0.008
Pre-event control mean	0.000	0.344	0.976	10.518
Observations	5,624,536	3,872,724	5,624,536	5,467,304
Nb. Unique Workers	117879	104402	117879	117874
Panel B: Firm-Level Outcomes				
	Firm Size	Firm AKM FE	Share Foreign	Share College
Post_{it}	-3,051.365***	0.032***	0.023***	0.012***
	(669.978)	(0.004)	(0.007)	(0.002)
$\text{Post}_{it} \times \text{Global}_i$	-5,781.714***	0.116***	0.180***	0.052***
	(927.560)	(0.018)	(0.033)	(0.006)
Treatment coef.	-8.8e+03	0.149	0.203	0.064
Treatment S.E.	1280.018	0.021	0.039	0.007
Pre-event control mean	1.9e+04	0.029	0.356	0.474
Observations	4,207,048	4,438,734	4,230,693	4,331,692
Nb. Unique Workers	106213	110575	106899	107632

Notes: This table shows estimates for the main specification, as given by Equation (1). The treatment coefficient is the sum of the Post_t and $\text{Post}_t \times \text{Global}_t$ coefficients. The pre-event control mean is the mean of the outcome variable among the control group in the time period before the event. Standard errors are in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.1$

pays all workers 11.6% more, as given by the firm AKM fixed effect.[8] Overall, this implies that gaining access to global remote firms increases pay for workers, largely via gaining access to a set of firms that pay workers more overall on average.

Next, we consider how the firms that workers enter differ in terms of other characteristics, as shown in Figure 3. Again, none of the outcomes we consider exhibit significant pre-trends. Column (1) of Panel (B) of Table 2 shows that joining a global firm is associated with joining a firm that employs significantly fewer workers (30%) compared to a traditional firm. Column (3) considers the share of workers at the firm that are located in the same country as the firm's headquarters versus another country. Switching jobs into a traditional firm only slightly changes the share of workers in a firm that are located outside the firm's country (by 2.3 percentage points), while switching into a global remote firm increases that share significantly, by another 18.0 percentage points, or 50.6% relative to the pre-event control mean.

Lastly, Column (4) considers a measure of coworker quality. Switching into a remote job increases the share of coworkers that have a college degree by 5.2 percentage points, or 11.0%. Furthermore, Table A1 shows that when workers switch jobs, the average world rank of their coworker's undergraduate institution improves by 33 ranks. However, when workers switch into a global remote job, the average rank improves by another 22 ranks.

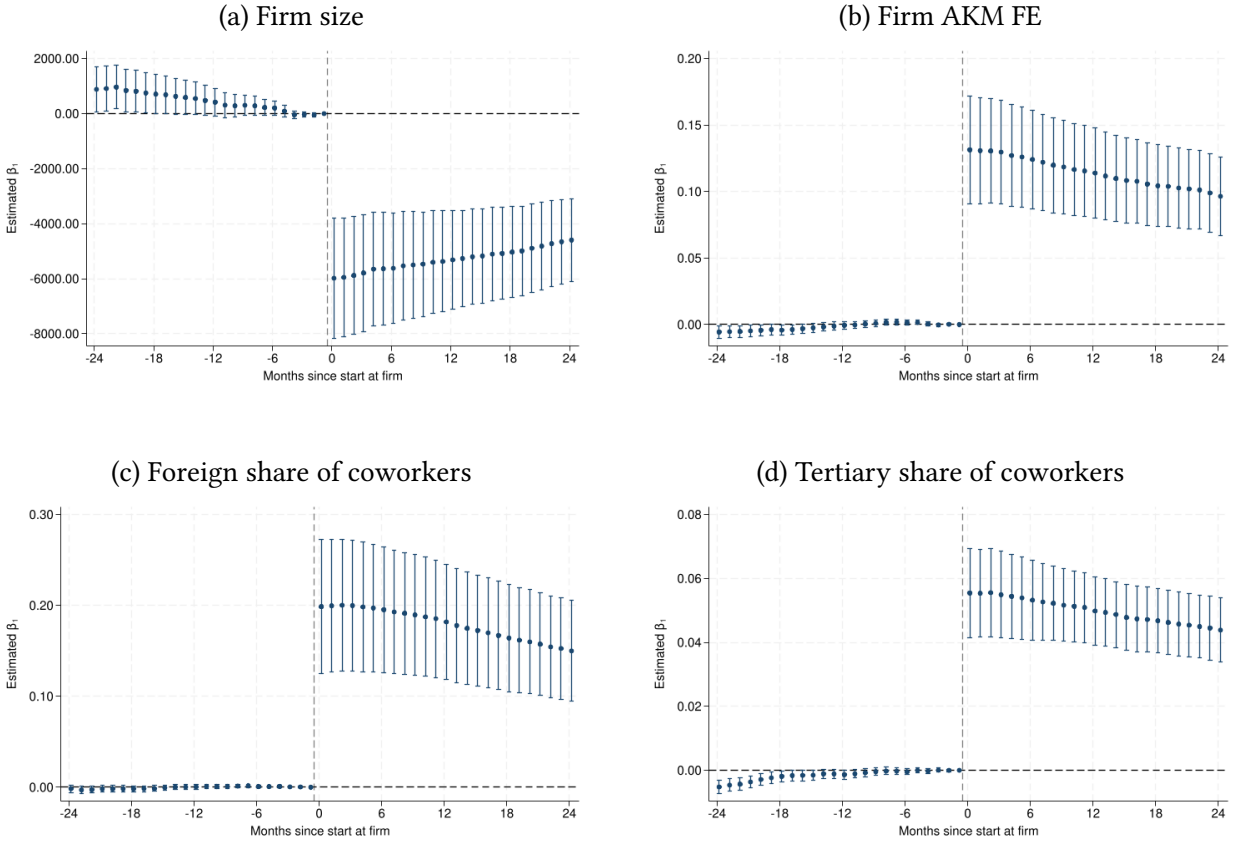
4.2 Heterogeneity

Table 3 show that the impacts on workers vary significantly by whether the worker is a domestic or foreign worker for the firm that they enter (see Figures A4 and A5 for the corresponding event study plots). In particular, we interact the treatment effect in equation (1) with whether or not the worker is in a country different from the home country of the firm they enter, which is held constant throughout the estimation sample.

As shown in Column (4) of Panel (A), both domestic and foreign workers receive significant pay increases when they enter into a global remote firm, although the increase is slightly larger for domestic workers. Columns (1) and (2) of Panel (B) show that both domestic and foreign workers enter into smaller and higher-paying firms overall, respectively. By joining a global remote firm, both domestic and foreign workers enter a firm that has a greater share of foreign workers than in their previous job (Column (3)), although that increase is greater for domestic workers than for foreign workers. Lastly, both domestic and foreign workers enter a firm that has more college-educated workers (Column (4)), with slight differences in the magnitudes.

[8] Appendix C.4 discusses how the firm AKM fixed effect is estimated.

Figure 3: Dynamic Firm-Level Treatment Effects on Workers



Notes: This figure show estimates of Equation (2) for various outcomes. All outcomes are firm-wide measures. The shares do not include the individual themselves, when applicable. For all panels, the treatment effect is shown in blue. Standard errors are clustered at the firm-level. 95% confidence intervals are shown.

Table 3: Heterogenous Impacts of Entering a Global Remote Firm on Workers

	(1)	(2)	(3)	(4)
Panel A: Worker-Level Outcomes				
	At Firm	Foreign Firm	Employed	log(Salary)
$Post_{it}$	0.825***	-0.213***	-0.002***	0.069***
	(0.001)	(0.010)	(0.000)	(0.004)
$Post_{it} \times Global_i$	-0.003***	0.082***	-0.006***	0.060***
	(0.001)	(0.014)	(0.000)	(0.008)
$Post_{it} \times Global_i \times Foreign_i$	0.016***	-0.048*	0.006***	-0.027***
	(0.001)	(0.028)	(0.001)	(0.008)
Foreign treatment coef.	0.013	0.034	-0.000	0.033
Foreign treatment S.E.	0.001	0.025	0.000	0.007
Pre-event control mean (domestic)	0.000	0.244	0.978	10.647
Pre-event control mean (foreign)	0.000	0.540	0.981	10.235
Observations	3,852,120	3,338,345	3,852,120	3,748,059
Nb. Unique Workers	80558	80558	80558	80556
Panel B: Firm-Level Outcomes				
	Firm Size	Firm AKM FE	Share Foreign	Share College
$Post_{it}$	-4,759.524***	0.008	-0.134***	0.017***
	(559.654)	(0.005)	(0.007)	(0.002)
$Post_{it} \times Global_i$	-5,202.208***	0.100***	0.195***	0.045***
	(1,169.637)	(0.015)	(0.019)	(0.006)
$Post_{it} \times Global_i \times Foreign_i$	-2,122.538*	0.011	-0.089***	0.019***
	(1,137.122)	(0.026)	(0.030)	(0.006)
Foreign treatment coef.	-7.3e+03	0.111	0.106	0.064
Foreign treatment S.E.	1223.035	0.027	0.038	0.007
Pre-event control mean (domestic)	1.8e+04	0.037	0.306	0.482
Pre-event control mean (foreign)	2.7e+04	0.059	0.462	0.515
Observations	3,341,330	3,439,551	3,392,932	3,448,268
Nb. Unique Workers	80040	80452	80446	80462

Notes: This table shows estimates of equation (1), split by whether the worker is a domestic or foreign worker. The worker is classified as foreign if the firm they enter is based in another country; the classification is held constant throughout the estimation sample. The foreign treatment coefficient equals the main treatment effect plus the interaction of the treatment effect with whether the worker is foreign. Control means in the pre-period are shown for both domestic and foreign workers. Standard errors are clustered at the firm-level and are shown in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

4.3 Robustness

Tables A2 and A3 consider various robustness checks. First, they consider specifications with just worker controls and omit the worker fixed effects. Second, they include fixed effects for an individual's matched group only (i.e., the worker that enters a global remote firm is directly compared to their observably-comparable worker) and then a fixed effect for the individual themselves (which is the main specification) for reference. The individual fixed effect is particularly insightful, as identification is now from within-person changes and all unobservable permanent worker differences in ability are absorbed. Neither fixed effect materially changes the estimate from without group or person fixed effects. Next, we relax various estimation sample restrictions: we consider all individuals regardless of whether they have data for the entire estimation sample, we consider unmatched individuals, and we limit to individuals that have stayed at their target job. The main estimates are stable across all specifications. Lastly, Tables A4 and A5 similarly show that the main heterogeneity analysis is robust to these various specifications.

5 Impacts on Downstream Career Outcomes

5.1 Impacts on workers that leave target firm

The previous section shows that entering a global remote firm increases income for workers and provides access to higher-paying and more-educated firms overall. Entering a global remote job may further have persistent impacts on human capital, thus affecting workers even after they leave their new firm. On the other hand, the impacts on workers documented above could be short-lived and vanish once workers leave their new firm. Similar, other contexts find significant increases in the returns to human capital and sustained gains in income (e.g., Amanzadeh et al. (2024); Prato (2025)).

Figure 4 shows the trajectories for workers that stay at their target firm compared to workers that leave their target firm, while Table A6 shows the underlying estimates. Panel (a) shows that after two years, workers that leave their target firm are still 2.1 percentage points (6%) more likely to be working for a foreign firm. While this is significantly less than the estimate for those that stay at their target firm, it is still significant, suggesting that gaining access to a global remote firm permanently alters the type of firm a worker pursues in the future. In terms of income, workers that leave their target firm still earn significantly more two years later. Panel (b) shows that workers still experience increased income when they leave their target firm, and that this increase grows over time.

Lastly, Figure 4 also shows that while impacts on firm-level characteristics decrease once treatment workers leave their target firm, they do remain significant. This finding is consistent

with the dynamic pattern of the firm-level outcomes as shown in Figure 3 above. Panel (c) shows that workers no longer are at smaller firms once they leave their target firm. However, workers remain at firms that pay more on average, have a larger share of foreign workers, and have a larger share of college-educated workers, as shown in Panels (d), (e), and (f), respectively.[9]

5.2 Climbing the job ladder

Next, we investigate how access to global remote work affects how individuals climb career ladders. Panel (a) of Figure 5 considers occupational switching, focusing on whether workers change positions within their new firm. By the end of two years, workers are 0.4 percentage points (or 50%) more likely to switch jobs within firms once they join a global firm. Panel (b) considers the distance of those occupational switches in terms of task content, as described above. While it takes time to materialize, workers experience larger changes in task content two years after joining a global remote firm, although not statistically significant.

5.3 Innovation

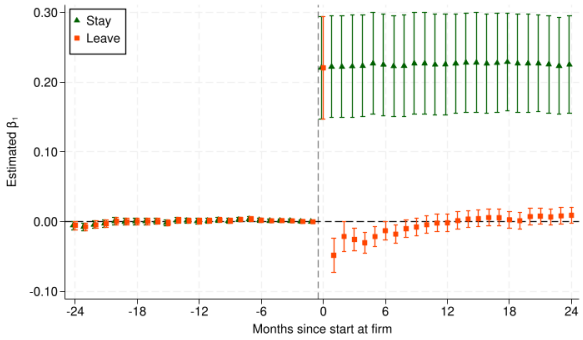
This section considers whether access to global firms has effects on a worker's propensity to innovate and start a new firm. First, Figure 6 plots point estimates of equation (1), considering how the share of coworkers at one's firm that have ever been a founder before changes when the individual switches jobs. The figure shows this for the entire sample (various specifications) and then by the size of the firm that the worker switches to. As shown in the main specification, when a control worker switches to a new firm they are exposed to 1.2 percentage points more founders. A treatment worker is exposed to an additional 0.6 percentage points more founders, for a total of 1.8 percentage points. This treatment effect represents a relative increase of 26% compared to the pre-event control mean. The treatment effect decreases slightly when controlling for firm size and is largest among workers that enter smaller firms.

Given that entering global remote firms increases exposure to innovators, we now consider whether this increase in exposure impacts the individual's own propensity to start a firm. We limit the sample to individuals that do not found their target firm. As shown in Table 4, 1.1% of workers have ever founded a company before switching jobs. Column (1) shows that entering a global remote firm increases the likelihood of becoming a founder in the next two years by 0.6 percentage points, or 57%. This treatment effect is robust to controlling for firm size or conditioning on never founding a firm before switching jobs. Finally, as shown in Columns (4) through (6), this effect is

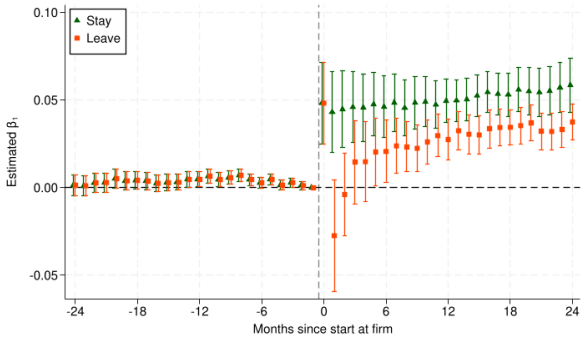
[9]Leaving the target firm is an endogenous decision, and so there is selection into whether a worker has stayed or left their target firm. Figure A6 attempts to mitigate that selection by only considering the sample of workers that eventually leave their target firm, although selection likely remains. Nevertheless, the figure shows qualitatively similar results as when considering all workers.

Figure 4: Treatment Effects on Workers: For Those that Stay at vs. Leave Target Firm

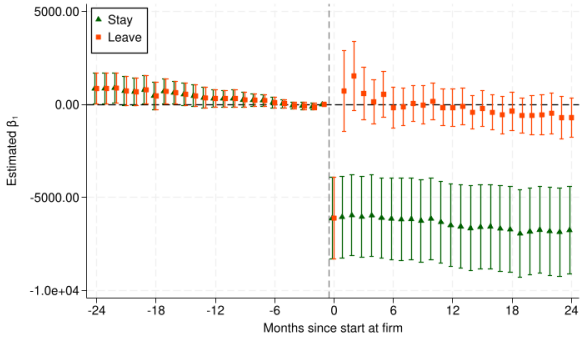
(a) Works for foreign firm



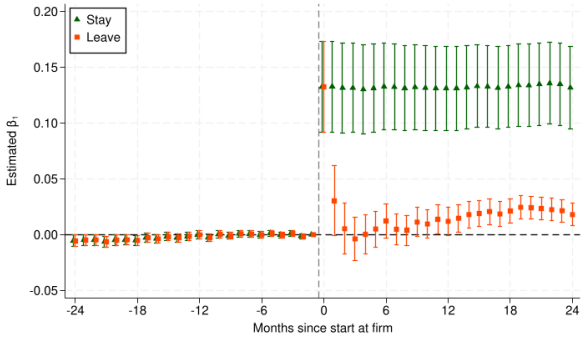
(b) Imputed individual earnings



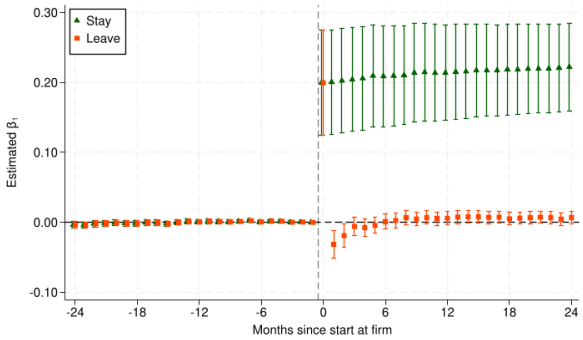
(c) Firm size



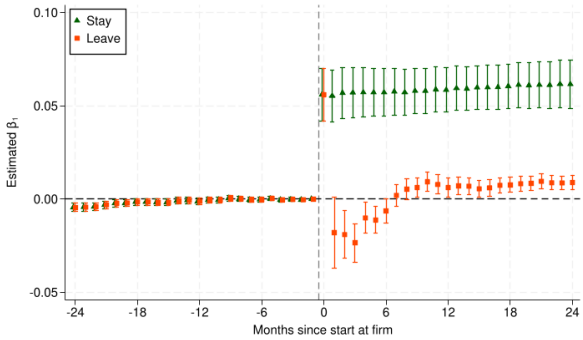
(d) Firm AKM fixed effect



(e) Foreign share of coworkers

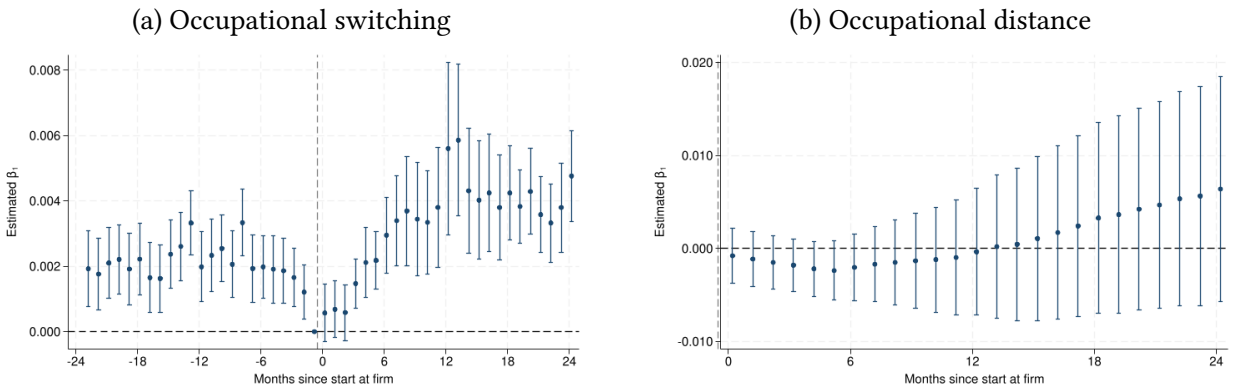


(f) Tertiary share of coworkers



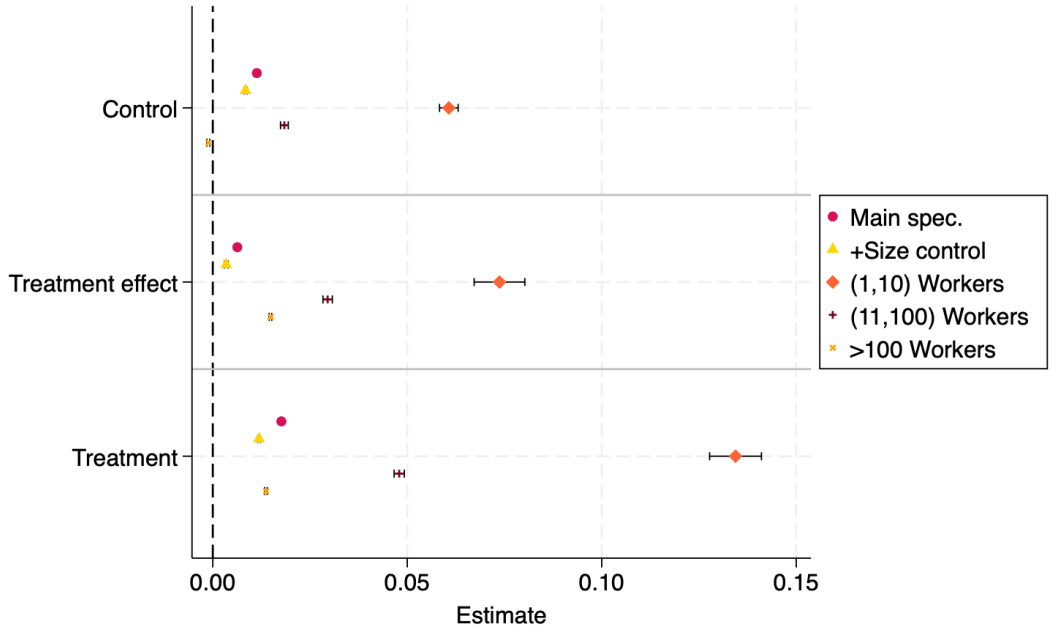
Notes: This figure show estimates of Equation (2) for various outcomes. Only the treatment effect is shown. The treatment effect is shown separately for those that stay in the target firm (green) and those that leave the target firm (orange). Standard errors are clustered at the firm-level. 95% confidence intervals are shown.

Figure 5: Impacts of Entering a Global Remote Firm on Occupational Ladders



Notes: This figure shows estimates of (2), where the outcomes variables are (a) whether the individual switches occupations and (b) the cumulative task distance in the worker's current occupation. See Appendix C.3 for more details on how the task distance is computed. Only the treatment effect is shown. Standard errors are clustered at the firm-level. 95% confidence intervals are shown.

Figure 6: Impacts of Entering a Global Remote Firm on Exposure to Founders



Notes: This figure plots estimates of equation (1), where the outcome variable is the leave-one-out share of coworkers that have ever been a founder of a firm before. The main empirical specification is shown, and then a specification including a control for firm size is included. The main specification is then estimated for various firm size buckets (1-10 workers, 11-100 workers, or more than 100 workers). Standard errors are clustered at the firm-level. 95% confidence intervals are shown.

largest when workers enter small firms, consistent with the fact that the increase in exposure to founders is largest in smaller firms.

Table 4: Impacts on Founding a Company

				Firm Size		
	(1)	(2)	(3)	(4)	(5)	(6)
	Main	Size Control	Never Founder	Small	Medium	Large
Post_{it}	-0.0036***	-0.0038***	-0.0017***	-0.0003	-0.0024***	-0.0044***
	(0.0001)	(0.0002)	(0.0001)	(0.0002)	(0.0003)	(0.0002)
$\text{Post}_{it} \times \text{Global}_i$	0.0063***	0.0066***	0.0027***	0.0110***	0.0083***	0.0063***
	(0.0001)	(0.0001)	(0.0001)	(0.0006)	(0.0004)	(0.0002)
Treatment coef.	0.0027	0.0028	0.0010	0.0107	0.0059	0.0019
Treatment S.E.	0.0001	0.0002	0.0001	0.0006	0.0004	0.0002
Pre-event control mean	0.0111	0.0123	0.0000	0.0044	0.0104	0.0122
Observations	1,389,779	1,244,693	1,371,669	152,237	182,037	1,055,502
Nb. Unique Workers	148187	145656	146316	16512	19632	112043

Notes: This table shows estimates of Equation (1). The outcome variable is whether the individual ever founds a company up until that point in time. Workers that found the firm they switch into are dropped from the estimation sample. Column (1) considers the main specification, Column (2) includes a firm size control, and Column (3) limits the sample to all workers that have never founded a firm when they make the job transition. Columns (4) through (6) estimate the main specification by firm size (1-10 workers, 11-100 workers, or more than 100 workers). Standard errors are clustered at the firm-level and are in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.1$

5.4 Executive experience

Table 5 considers impacts on another measure of career progression: whether the worker enters an executive position. In particular, executive positions are defined as any executive, director, or vice president jobs (see Appendix C.3.1 for the exact definition). As shown in Column (1), access to global firms increases the likelihood that workers eventually become an executive in the two years following the job transition by 1.5 percentage points or 80%. This estimate is similarly robust to controlling for firm size or limiting to workers that have never held an executive position before, and is driven by workers that enter small firms.

Table 5: Impacts on Becoming an Executive

				Firm Size		
	(1)	(2)	(3)	(4)	(5)	(6)
	Main	Size Control	Never Executive	Small	Medium	Large
$Post_{it}$	-0.0037***	-0.0039***	-0.0025***	0.0014***	-0.0036***	-0.0049***
	(0.0002)	(0.0002)	(0.0001)	(0.0004)	(0.0006)	(0.0003)
$Post_{it} \times Global_i$	0.0150***	0.0159***	0.0036***	0.0640***	0.0306***	0.0140***
	(0.0002)	(0.0002)	(0.0001)	(0.0012)	(0.0006)	(0.0002)
Treatment coef.	0.0112	0.0120	0.0011	0.0654	0.0270	0.0091
Treatment S.E.	0.0002	0.0002	0.0001	0.0012	0.0007	0.0002
Pre-event control mean	0.0187	0.0202	0.0000	0.0054	0.0175	0.0208
Observations	1,389,779	1,244,693	1,354,361	152,237	182,037	1,055,502
Nb. Unique Workers	148187	145656	144551	16512	19632	112043

Notes: This table shows estimates of Equation (1). The outcome variable is whether the individual ever holds an executive position up until that point in time. An executive position is defined as any executive, director, or vice president job. Workers that hold an executive position in the firm they switch into are dropped from the estimation sample. Column (1) considers the main specification, Column (2) includes a firm size control, and Column (3) limits the sample to all workers that have never been an executive before when they make the job transition. Columns (4) through (6) estimate the main specification by firm size (1-10 workers, 11-100 workers, or more than 100 workers). Standard errors are clustered at the firm-level and are in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.1$

6 Conclusion

This paper provides evidence on the impacts of global remote work on workers from around the world. Access to global remote firms increases imputed income for workers, relative to similar workers that switch into a traditional, non-remote firm. Access to these firms also materially changes the types of firms workers enter, leading workers into firms that pay more on average, are smaller, have more foreign workers, and have more college-educated workers. These impacts do not vanish once workers leave their new job, but rather result in sustained improvements in career trajectories. Workers continue to earn more, in addition to climbing occupational ladders more quickly. Workers also are more likely to eventually become a founder or enter an executive position after they leave their target firm. Finally, these impacts are significant for both domestic and foreign workers in general.

Global remote work is a relatively new and growing mode of hiring, and is one way in which the labor market is currently undergoing rapid technological change. Further understanding the mechanisms behind the impacts of global remote work, in addition to the impacts on firm growth and productivity, remain an open and important question for future research.

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A Appendix Tables

Table A1: Other Measures of Coworker Quality

	(1) Share College	(2) University Ranking
Post_{it}	0.012***	-32.574***
	(0.002)	(2.677)
$\text{Post}_{it} \times \text{Global}_i$	0.052***	-22.392***
	(0.006)	(3.329)
Treatment coef.	0.064	-54.966
Treatment S.E.	0.007	4.844
Pre-event control mean	0.474	576.338
Observations	4,331,692	4,221,627
Nb. Unique Workers	107632	107207

Notes: This table shows estimates for the main specification, as given by Equation (1), for various measures of coworker quality. The treatment coefficient is the sum of the Post_t and $\text{Post}_t \times \text{Global}_t$ coefficients. The pre-event control mean is the mean of the outcome variable among the control group in the time period before the event. Standard errors are in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table A2: Average Worker-Level Impacts on Workers: Robustness Checks

	(1) Main	(2) Group FE	(3) Person FE	(4) Unbalanced	(5) Unmatched	(6) Stayed
Panel A: Outcome: At Firm						
$Post_{it}$	0.842***	0.899***	1.017***	1.010***	1.017***	1.000***
	(0.004)	(0.004)	(0.007)	(0.005)	(0.007)	(0.000)
$Post_{it} \times Global_i$	0.027	0.025	0.024	0.024	0.024	-0.000***
	(0.037)	(0.033)	(0.025)	(0.024)	(0.025)	(0.000)
Observations	5,467,808	5,467,807	5,467,803	7,929,380	5,543,856	5,467,803
Panel B: Outcome: Foreign Firm						
$Post_{it}$	0.030***	0.041***	0.057***	0.049***	0.057***	0.018***
	(0.008)	(0.008)	(0.007)	(0.006)	(0.007)	(0.005)
$Post_{it} \times Global_i$	0.199***	0.193***	0.184***	0.186***	0.185***	0.224***
	(0.046)	(0.043)	(0.034)	(0.032)	(0.034)	(0.036)
Observations	3,872,724	3,872,661	3,872,315	5,542,697	3,935,092	3,872,315
Panel C: Outcome: Employed						
$Post_{it}$	0.050***	0.080***	0.186***	0.034***	0.049***	0.188***
	(0.000)	(0.000)	(0.001)	(0.000)	(0.000)	(0.000)
$Post_{it} \times Global_i$	-0.002***	-0.001	-0.048***	0.001**	-0.001**	-0.060***
	(0.001)	(0.001)	(0.001)	(0.000)	(0.000)	(0.000)
Observations	6,656,395	6,656,393	6,656,386	10,094,833	6,848,787	6,656,395
Panel D: Outcome: log(Salary)						
$Post_{it}$	0.090***	0.096***	0.076***	0.061***	0.076***	0.031***
	(0.005)	(0.004)	(0.004)	(0.003)	(0.004)	(0.003)
$Post_{it} \times Global_i$	0.048**	0.046***	0.044***	0.047***	0.043***	0.048***
	(0.024)	(0.015)	(0.006)	(0.006)	(0.006)	(0.007)
Observations	5,467,309	5,467,308	5,467,304	7,928,641	5,543,355	5,467,304

Notes: This table shows various robustness checks of the main empirical specification, as given by (1). The main worker-level outcomes are shown. Column (1) omits person fixed effects, Column (2) includes matched-pair fixed effects, and Column (3) includes person fixed effects, which is the preferred specification. Column (4) does not limit the sample to the balanced panel, including individuals that do not have data for the entire period. Column (5) includes treatment workers for which they do not have a matched pair. Column (6) limits the sample to workers that stay in their target firm. Controls include month, country, and person fixed effects. The standard errors are clustered at firm-level and shown in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table A3: Average Firm-Level Impacts on Workers: Robustness Checks

	(1) Main	(2) Group FE	(3) Person FE	(4) Unbalanced	(5) Unmatched	(6) Stayed
Panel A: Outcome: Firm Size						
$Post_{it}$	-2,135.725*	-2,606.462**	-3,051.365***	-3,096.054***	-3,051.163***	-1,712.510***
	(1,169.130)	(1,110.062)	(669.978)	(569.775)	(670.866)	(514.795)
$Post_{it} \times Global_i$	-4,977.322**	-5,270.535***	-5,781.714***	-5,379.509***	-5,642.583***	-6,348.644***
	(2,251.802)	(1,532.969)	(927.560)	(875.084)	(923.048)	(1,053.756)
Observations	4,207,386	4,207,363	4,207,048	6,037,276	4,281,491	4,207,048
Panel B: Outcome: Firm AKM FE						
$Post_{it}$	0.028***	0.027***	0.032***	0.025***	0.032***	0.007**
	(0.006)	(0.004)	(0.004)	(0.004)	(0.004)	(0.003)
$Post_{it} \times Global_i$	0.120***	0.118***	0.116***	0.119***	0.116***	0.132***
	(0.032)	(0.024)	(0.018)	(0.019)	(0.018)	(0.020)
Observations	4,439,029	4,438,995	4,438,734	6,388,542	4,507,354	4,438,734
Panel C: Outcome: Share Foreign						
$Post_{it}$	0.006	0.011	0.023***	0.022***	0.023***	-0.004
	(0.007)	(0.007)	(0.007)	(0.005)	(0.007)	(0.003)
$Post_{it} \times Global_i$	0.187***	0.185***	0.180***	0.184***	0.182***	0.213***
	(0.055)	(0.046)	(0.033)	(0.030)	(0.033)	(0.035)
Observations	4,231,051	4,231,011	4,230,693	6,081,866	4,299,954	4,230,693
Panel D: Outcome: Share College						
$Post_{it}$	0.008***	0.010***	0.012***	0.010***	0.012***	0.001
	(0.003)	(0.002)	(0.002)	(0.002)	(0.002)	(0.001)
$Post_{it} \times Global_i$	0.049***	0.050***	0.052***	0.054***	0.052***	0.060***
	(0.015)	(0.009)	(0.006)	(0.006)	(0.006)	(0.006)
Observations	4,332,029	4,331,995	4,331,692	6,225,370	4,403,534	4,331,692

Notes: This table shows various robustness checks of the main empirical specification, as given by (1). The main firm-level outcomes are shown. Column (1) omits person fixed effects, Column (2) includes matched-pair fixed effects, and Column (3) includes person fixed effects, which is the preferred specification. Column (4) does not limit the sample to the balanced panel, including individuals that do not have data for the entire period. Column (5) includes treatment workers for which they do not have a matched pair. Column (6) limits the sample to workers that stay in their target firm. Controls include month, country, and person fixed effects. The standard errors are clustered at the firm-level and shown in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table A4: Heterogenous Worker-Level Impacts on Workers: Robustness Checks

	(1) Main	(2) Group FE	(3) Person FE	(4) Unbalanced	(5) Unmatched	(6) Stayed
Panel A: Outcome: At Firm						
$Post_{it}$	0.844***	0.910***	1.031***	1.025***	1.031***	1.000***
	(0.005)	(0.005)	(0.006)	(0.004)	(0.006)	(0.000)
$Post_{it} \times Global_i$	0.000	-0.001	-0.005	-0.006	-0.006	0.000***
	(0.039)	(0.034)	(0.026)	(0.026)	(0.026)	(0.000)
$Post_{it} \times Global_i \times Foreign_i$	0.011	0.011	0.013	0.014	0.014	0.000
	(0.048)	(0.043)	(0.035)	(0.032)	(0.034)	(0.000)
Observations	3,748,481	3,748,480	3,748,479	5,240,949	3,813,695	3,748,479
Panel B: Outcome: Foreign Firm						
$Post_{it}$ $Post_{it}$	-0.213***	-0.213***	-0.244***	-0.246***	-0.244***	-0.247***
	(0.010)	(0.010)	(0.008)	(0.007)	(0.008)	(0.007)
$Post_{it} \times Global_i$	0.082***	0.081***	0.083***	0.083***	0.082***	0.099***
	(0.014)	(0.014)	(0.014)	(0.015)	(0.014)	(0.017)
$Post_{it} \times Global_i \times Foreign_i$	-0.048*	-0.048*	-0.049	-0.055*	-0.050*	-0.062**
	(0.028)	(0.027)	(0.030)	(0.028)	(0.030)	(0.024)
Observations	3,338,345	3,338,302	3,338,205	4,649,150	3,396,462	3,338,205
Panel C: Outcome: Employed						
$Post_{it}$	0.050***	0.080***	0.186***	0.034***	0.049***	0.188***
	(0.000)	(0.000)	(0.001)	(0.000)	(0.000)	(0.000)
$Post_{it} \times Global_i$	-0.002***	-0.001	-0.048***	0.001**	-0.001**	-0.060***
	(0.001)	(0.001)	(0.001)	(0.000)	(0.000)	(0.000)
$Post_{it} \times Global_i \times Foreign_i$	-0.002***	-0.001	-0.048***	0.001**	-0.001**	-0.060***
	(0.001)	(0.001)	(0.001)	(0.000)	(0.000)	(0.000)
Observations	6,656,395	6,656,393	6,656,386	10,094,833	6,848,787	6,656,395
Panel D: Outcome: log(Salary)						
$Post_{it}$	0.077***	0.086***	0.069***	0.051***	0.069***	0.025***
	(0.008)	(0.006)	(0.004)	(0.003)	(0.004)	(0.004)
$Post_{it} \times Global_i$	0.067**	0.062***	0.060***	0.071***	0.060***	0.069***
	(0.027)	(0.016)	(0.008)	(0.008)	(0.008)	(0.009)
$Post_{it} \times Global_i \times Foreign_i$	-0.031	-0.027	-0.027***	-0.040***	-0.028***	-0.034***
	(0.033)	(0.017)	(0.008)	(0.008)	(0.008)	(0.010)
Observations	3,748,061	3,748,060	3,748,059	5,240,366	3,813,273	3,748,059

Notes: This table shows various robustness checks of the main empirical specification, as given by (1). This table considers worker-level heterogeneous effects, as shown in Table 3. Column (1) omits person fixed effects, Column (2) includes matched-pair fixed effects, and Column (3) includes person fixed effects, which is the preferred specification. Column (4) does not limit the sample to the balanced panel, including individuals that do not have data for the entire period. Column (5) includes treatment workers for which they do not have a matched pair. Column (6) limits the sample to workers that stay in their target firm. Controls include month, country, and person fixed effects. The standard errors are clustered at the firm-level and shown in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table A5: Heterogenous Firm-Level Impacts on Workers: Robustness Checks

	(1) Main	(2) Group FE	(3) Person FE	(4) Unbalanced	(5) Unmatched	(6) Stayed
Panel A: Outcome: Firm Size						
$Post_{it}$	-4,587.184***	-4,537.869***	-4,759.524***	-4,716.272***	-4,756.915***	-3,673.796***
	(1,208.138)	(1,040.075)	(559.654)	(497.754)	(559.122)	(518.539)
$Post_{it} \times Global_i$	-4,069.282*	-4,459.166**	-5,202.208***	-4,596.481***	-5,147.976***	-5,940.180***
	(2,143.307)	(1,803.229)	(1,169.637)	(1,092.278)	(1,162.668)	(1,271.165)
$Post_{it} \times Global_i \times Foreign_i$	-498.999	-773.250	-2,122.538*	-2,517.189**	-1,928.203*	-2,530.252**
	(2,122.839)	(1,652.198)	(1,137.122)	(1,126.502)	(1,118.741)	(1,266.550)
Observations	3,341,435	3,341,416	3,341,330	4,652,477	3,405,129	3,341,330
Panel B: Outcome: Firm AKM FE						
$Post_{it}$	0.004	0.004	0.008	0.002	0.008	-0.016***
	(0.009)	(0.007)	(0.005)	(0.005)	(0.006)	(0.005)
$Post_{it} \times Global_i$	0.107***	0.105***	0.100***	0.105***	0.099***	0.117***
	(0.032)	(0.025)	(0.015)	(0.015)	(0.015)	(0.017)
$Post_{it} \times Global_i \times Foreign_i$	0.013	0.009	0.011	0.015	0.010	0.006
	(0.046)	(0.036)	(0.026)	(0.026)	(0.026)	(0.029)
Observations	3,439,648	3,439,616	3,439,551	4,797,827	3,498,727	3,439,551
Panel C: Outcome: Share Foreign						
$Post_{it}$	-0.134***	-0.131***	-0.134***	-0.134***	-0.133***	-0.149***
	(0.010)	(0.009)	(0.007)	(0.006)	(0.007)	(0.006)
$Post_{it} \times Global_i$	0.208***	0.203***	0.195***	0.199***	0.195***	0.236***
	(0.039)	(0.029)	(0.019)	(0.019)	(0.019)	(0.023)
$Post_{it} \times Global_i \times Foreign_i$	-0.099**	-0.098**	-0.089***	-0.092***	-0.087***	-0.113***
	(0.047)	(0.038)	(0.030)	(0.029)	(0.030)	(0.030)
Observations	3,393,044	3,393,011	3,392,932	4,728,656	3,452,633	3,392,932
Panel D: Outcome: Share College						
$Post_{it}$	0.009***	0.013***	0.017***	0.015***	0.017***	0.007***
	(0.003)	(0.002)	(0.002)	(0.002)	(0.002)	(0.001)
$Post_{it} \times Global_i$	0.049***	0.047***	0.045***	0.047***	0.045***	0.054***
	(0.014)	(0.010)	(0.006)	(0.006)	(0.006)	(0.007)
$Post_{it} \times Global_i \times Foreign_i$	0.020	0.019**	0.019***	0.020***	0.020***	0.018**
	(0.013)	(0.008)	(0.006)	(0.006)	(0.006)	(0.008)
Observations	3,448,360	3,448,337	3,448,268	4,804,171	3,510,026	3,448,268

Notes: This table shows various robustness checks of the main empirical specification, as given by (1). This table considers firm-level heterogeneous effects, as shown in Table 3. Column (1) omits person fixed effects, Column (2) includes matched-pair fixed effects, and Column (3) includes person fixed effects, which is the preferred specification. Column (4) does not limit the sample to the balanced panel, including individuals that do not have data for the entire period. Column (5) includes treatment workers for which they do not have a matched pair. Column (6) limits the sample to workers that stay in their target firm. Controls include month, country, and person fixed effects. The standard errors are clustered at the firm-level and shown in parentheses. *** p<0.01, ** p<0.05, * p<0.1

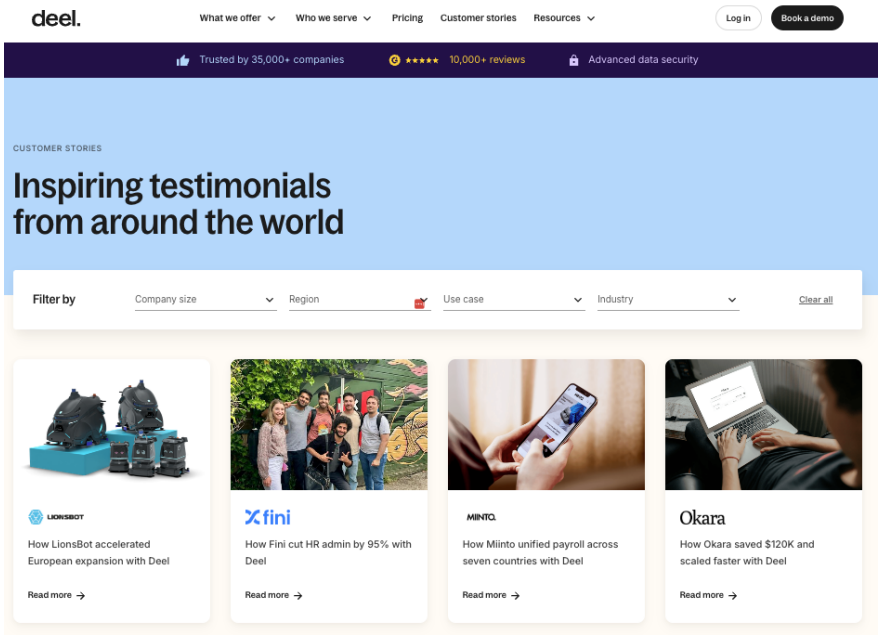
Table A6: Average Impacts on Workers: For Those that Stay at vs. Leave Target Firm

	(1)	(2)	(3)	(4)
Panel A: Worker-Level Outcomes				
	At Firm	Foreign Firm	Employed	log(Salary)
$Post_{it}$	0.000	0.002	-0.120***	0.088***
	(0.000)	(0.009)	(0.000)	(0.005)
$Post_{it} \times Global_i$	0.000	0.021***	-0.028***	0.017***
	(0.000)	(0.008)	(0.000)	(0.005)
$Post_{it} \times Global_i \times Stay_{it}$	-0.000	0.216***	0.024***	0.032***
	(0.000)	(0.047)	(0.000)	(0.009))
Stay coef.	0.000	0.236	-0.004	0.049
Stay S.E.	0.000	0.047	0.000	0.007
Pre-event control mean	0.000	0.344	0.976	10.518
Observations	5,624,536	3,872,724	5,624,536	5,467,304
Nb. Unique Workers	117879	104402	117879	117874
Panel B: Firm-Level Outcomes				
	Firm Size	Firm AKM FE	Share Foreign	Share College
$Post_{it}$	-933.584*	0.018***	0.001	0.008***
	(550.050)	(0.004)	(0.005)	(0.003)
$Post_{it} \times Global_i$	-1,571.440***	0.019***	0.002	0.005**
	(410.241)	(0.006)	(0.005)	(0.002)
$Post_{it} \times Global_i \times Stay_{it}$	-4,919.737***	0.115***	0.211***	0.056***
	(1,002.128)	(0.021)	(0.036)	(0.007)
Stay coef.	-6.5e+03	0.134	0.213	0.061
Stay S.E.	1065.773	0.019	0.035	0.006
Pre-event control mean	1.9e+04	0.029	0.356	0.474
Observations	4,207,048	4,438,734	4,230,693	4,331,692
Nb. Unique Workers	106213	110575	106899	107632

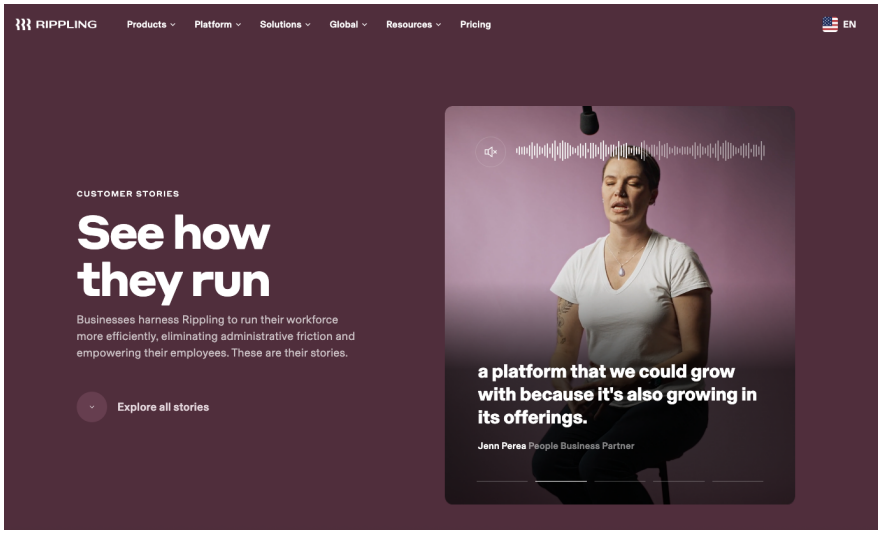
Notes: This table shows the underlying estimates of Figure 4. The main empirical specification is shown. The treatment is interacted with whether or not the worker stays at their target firm in the given time period. The stay treatment coefficient equals the main treatment effect plus the interaction of the treatment effect with whether the worker is still at their target firm. The standard errors are clustered at the firm-level and shown in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.1$

B Appendix Figures

Figure A1: Examples of Scraped Data: Screenshots of Global Human Resources Firms



(a) Deel Testimonials

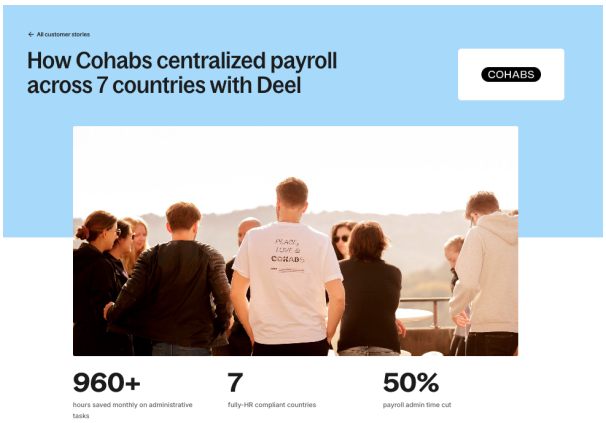


(b) Rippling Testimonials

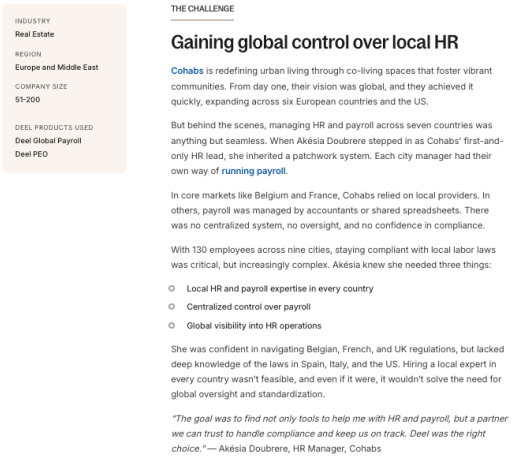
Notes: These figures show screenshots of lists of case studies for clients from both Deel and Rippling in Panels (a) and (b), respectively.

Figure A2: Examples of Scraped Data: Screenshots of Clients

(a) Deel Firm Example



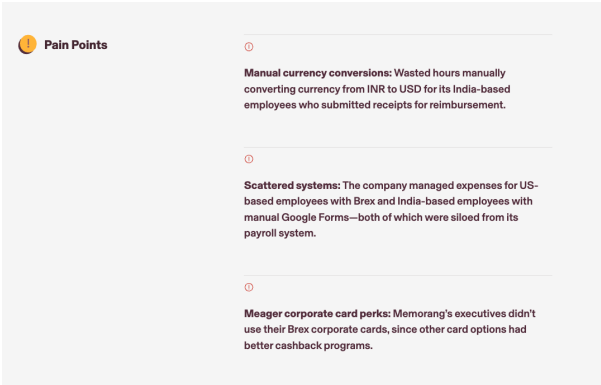
(b) Deel Firm Example (Cont.)



(c) Rippling Firm Example

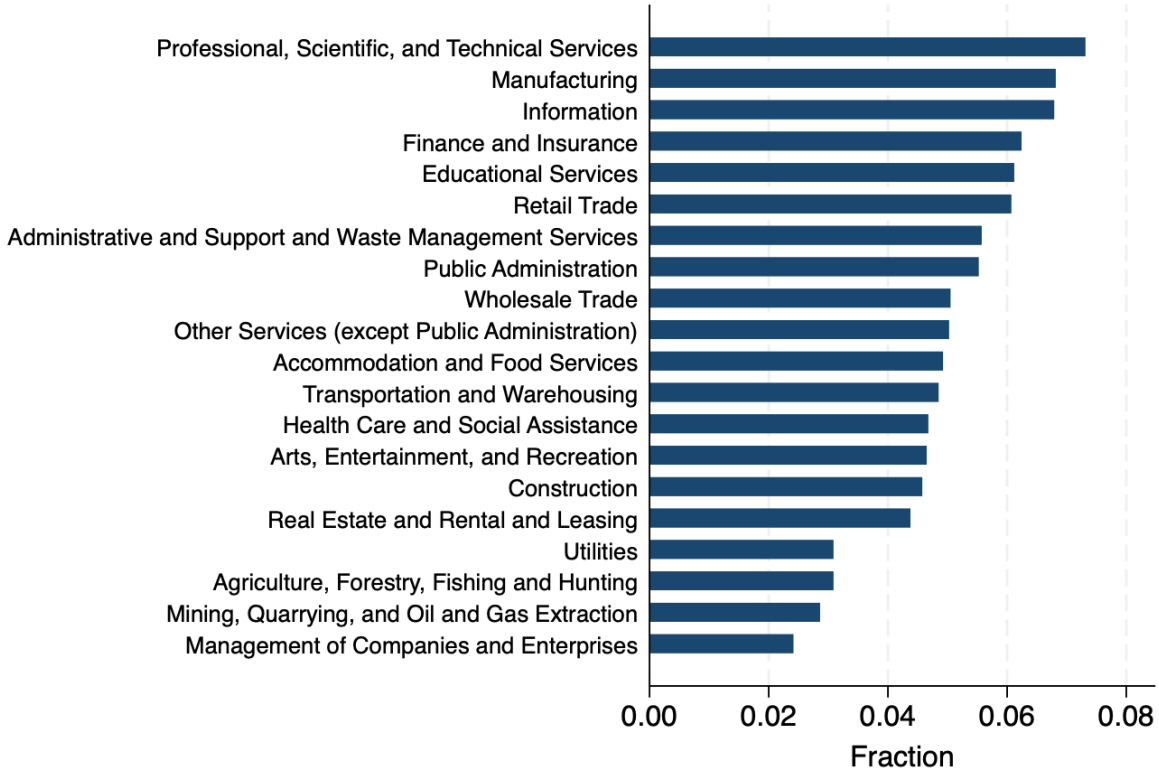


(d) Rippling Firm Example (Cont.)



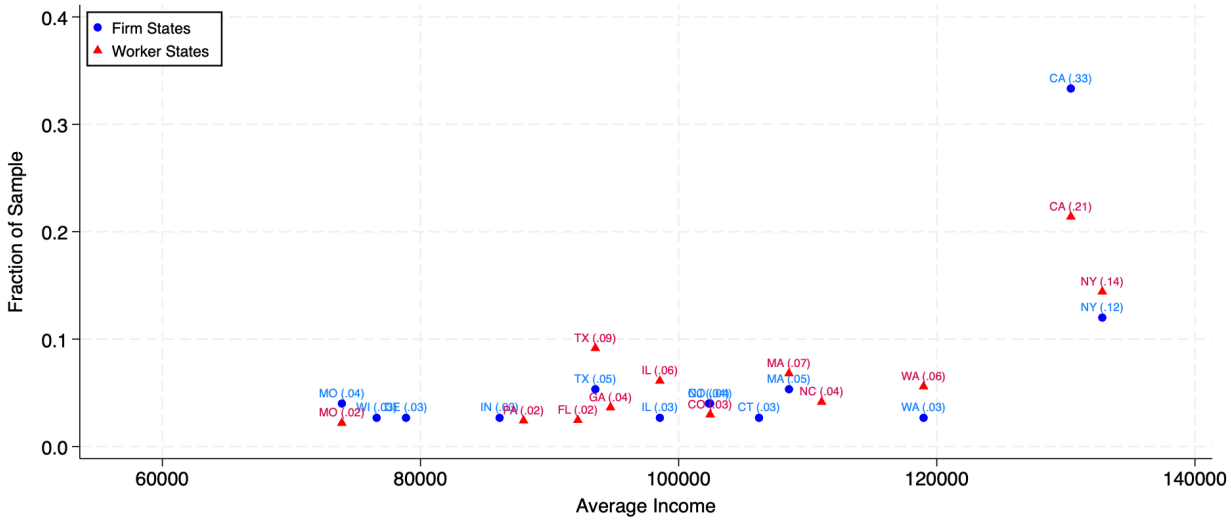
Notes: These figures show screenshots of specific examples of clients that use Deel and Rippling. Panels (a) and (b) show the firm Cohabs, which is a client of Deel. Panels (c) and (d) show the firm Memorang, which is a client of Rippling.

Figure A3: Industry Composition of Firms



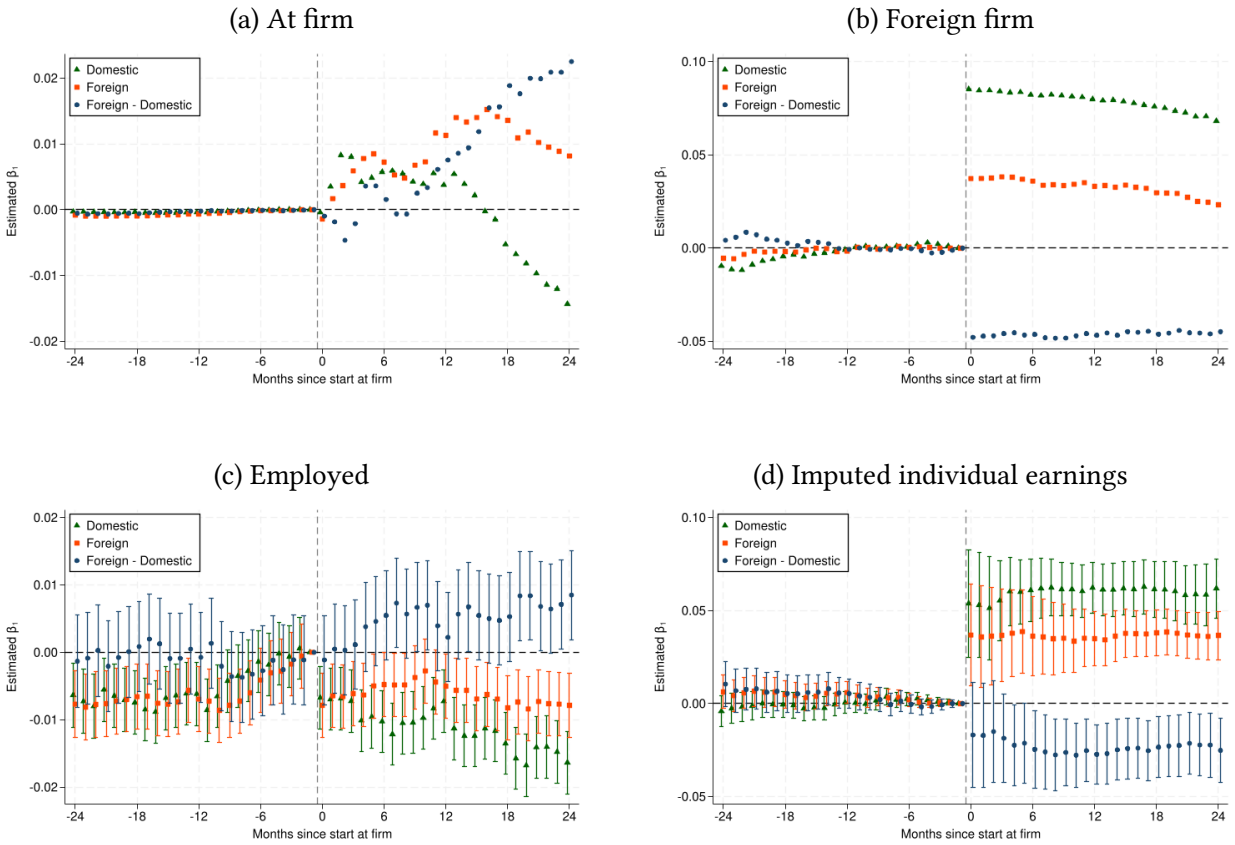
Notes: This figure shows the industry composition of firms in the main sample. The distribution is not weighted by firm size. The classification uses two-digit North American Industry Classification System (NAICS) codes. Only industries with at least 1% of the sample are shown for exposition.

Figure A4: Worker and Firm Locations in the United States



Notes: This figure shows the distribution of worker locations and firm locations by state in the United States. States are sorted by their average worker salary. Blue dots show locations of firm states and red dots show locations of worker states. Only states with greater than 1% in either category are shown. The firm distribution is not weighted by firm size.

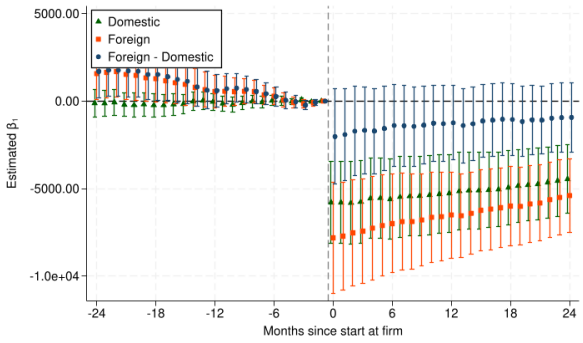
Figure A4: Heterogenous Worker-Level Treatment Effects on Workers



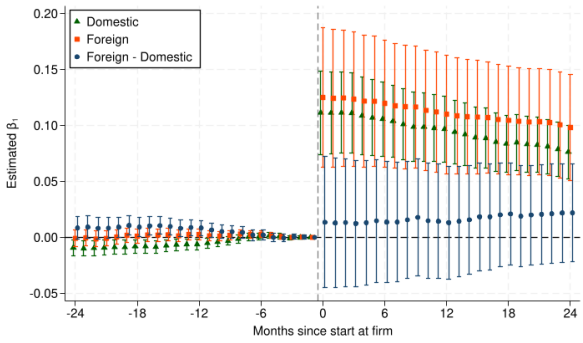
Notes: Figures show estimates of Equation (2) for various outcomes, split by whether the worker enters the firm as a domestic or foreign worker. Green refers to the treatment effect among domestic workers, blue refers to the treatment effect among foreign workers, and black refers to the difference between the treatment effect for foreign workers compared to domestic workers. 95% confidence intervals are shown.

Figure A5: Heterogenous Firm-Level Treatment Effects on Workers

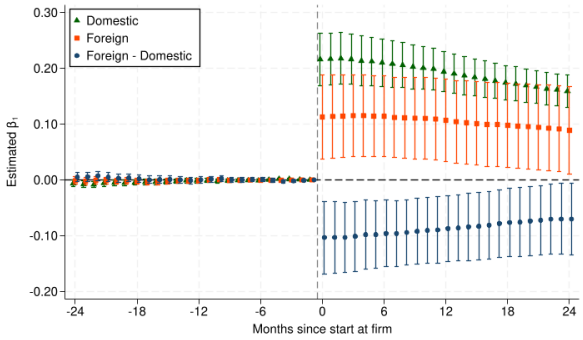
(a) Firm size



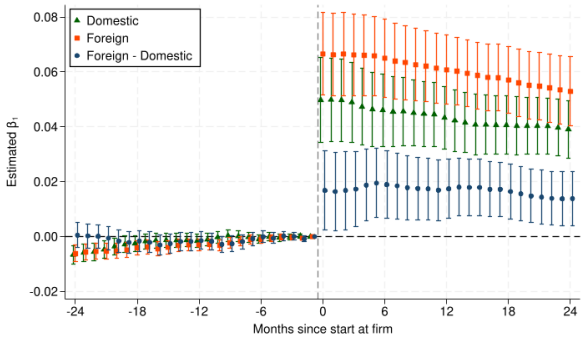
(b) Firm AKM fixed effect



(c) Foreign share of coworkers



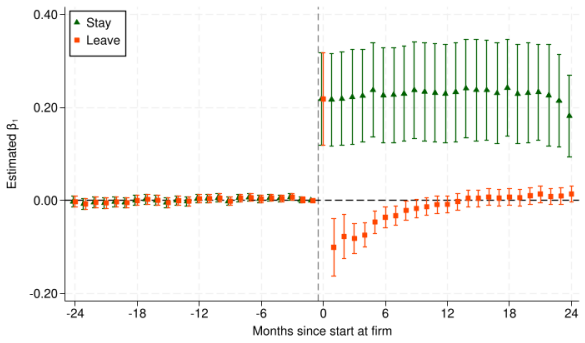
(d) Bachelor's share of coworkers



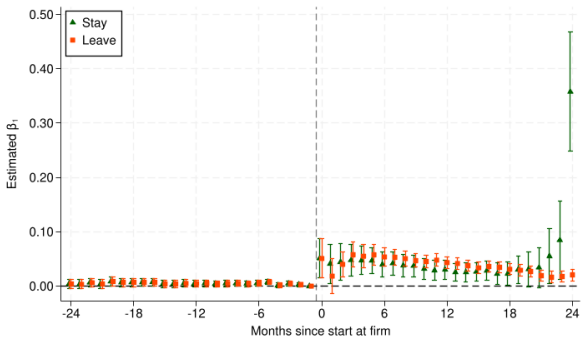
Notes: Figures show estimates of Equation (2) for various outcomes, split by whether the worker enters the firm as a domestic or foreign worker. Green refers to the treatment effect among domestic workers, blue refers to the treatment effect among foreign workers, and black refers to the difference between the treatment effect for foreign workers compared to domestic workers. 95% confidence intervals are shown.

Figure A6: Treatment Effects on Workers: For Those that Stay at vs. Leave Target Firm, Conditional on Leaving

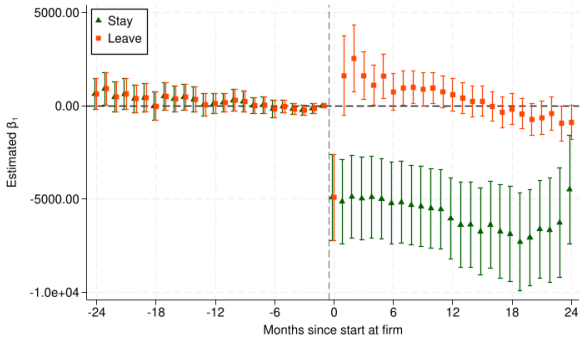
(a) Foreign firm



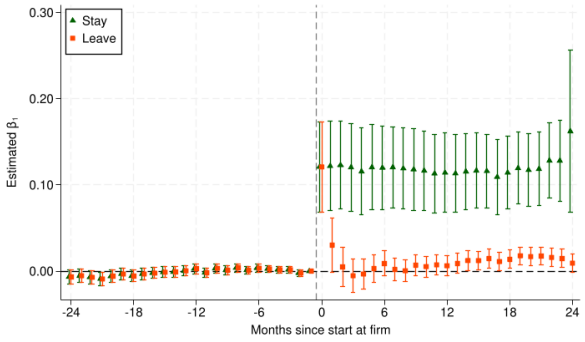
(b) Imputed individual earnings



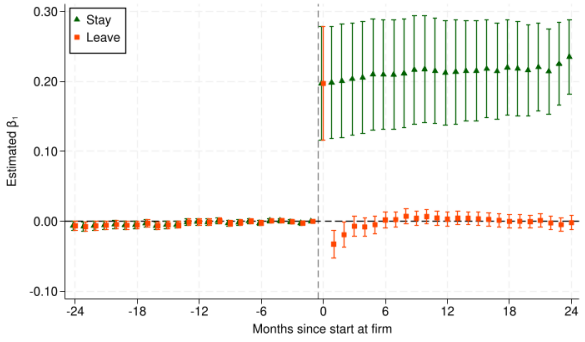
(c) Firm size



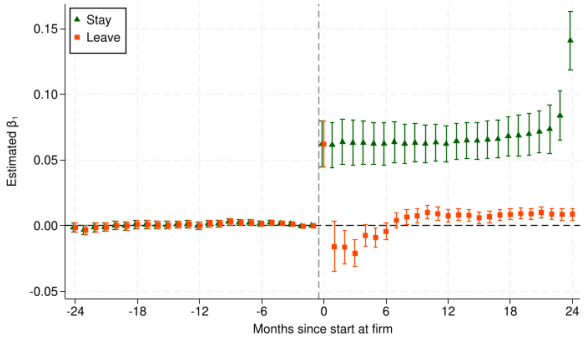
(d) Firm AKM fixed effect



(e) Foreign share of coworkers



(f) Tertiary share of coworkers



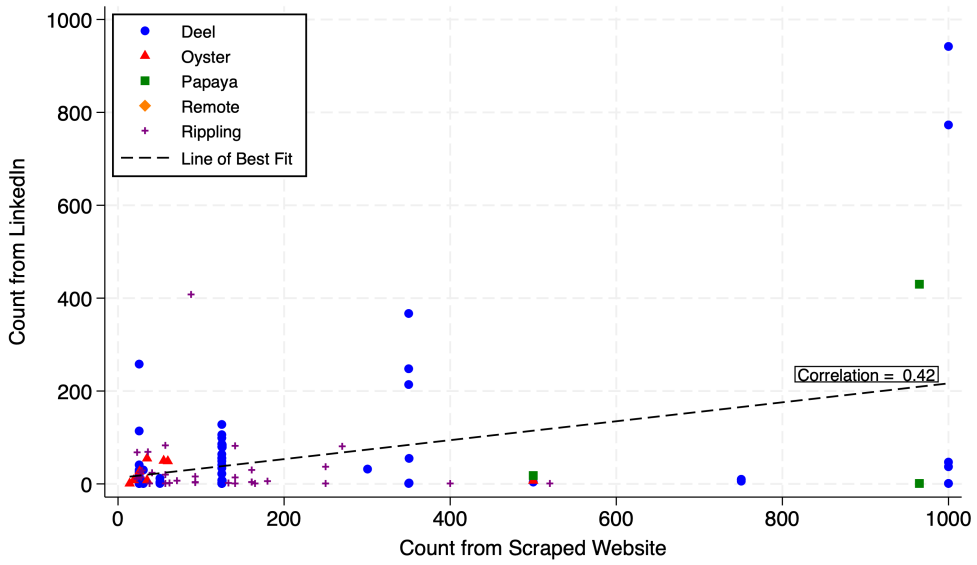
Notes: This figure shows estimates of Equation (2) for various outcomes. Only the treatment effect is shown. The treatment effect is shown separately for those that stay in the target firm (green) and those that leave the target firm (orange). In contrast to Figure 4, the sample is limited to workers that leave their target firm at some point in the two years after making the initial job transition. Standard errors are clustered at the firm-level. 95% confidence intervals are shown.

C More Details about Data

C.1 Firm sampling frame

We use data on 322 firms from 5 different intermediaries: 157 from Deel, 17 from Oyster HR, 20 from Papaya, 34 from Remote, and 94 from Rippling. We then compare the firm counts advertised on the intermediarie's websites with the number of unique workers found in the LinkedIn data. As shown in Figure A7, these counts broadly align with each other, with a correlation of 0.42.

Figure A7: Data Validation Exercise



Notes: This figure shows firm counts from the LinkedIn data and from the scraped intermediary website. The figure only shows firms with 1,000 workers or less.

C.2 Details regarding LinkedIn data

In terms of the education data, we observe any education histories that are self-reported by a LinkedIn user. This includes university name, university location, degree name, and major. We categorize degrees into bachelor's degrees and graduate degrees (which include master's degrees and doctorate degrees). When education end years are missing, we impute them from the start year for the purposes of determining age.[10] We also assign each undergraduate university their

[10]We assume typical graduation ages by degree type: 18 for a high school degree, 21 for an associate's degree, 22 for a bachelor's degree, 24 for a master's degree or an MBA, 26 for doctorate degree, and 23 for other degrees. For individuals with multiple degrees, we use the lowest degree completed. For workers that report no education data, we assume they began working at age 18 and impute age from their earliest observed employment start date.

ranking from the 2022 Times Higher Education World University Rankings, as provided by Revelio Labs.

LinkedIn users report their employment through position postings. Our work concerns the universe of postings from 2016 to 2024. Users self-report their employer's name and their job title, as well as the city, state, and country of their position.[11] Revelio Labs reports the employing firms' headquarters location and their North American Industry Classification System (NAICS) industry code. Users also self-report their position start and end dates, at the monthly level. For each position, Revelio Labs estimates an annual salary based on their own regression-based model, which is a function of various worker, firm, and job characteristics, including position titles, seniority, and the company. We deflate salaries to December 2024 dollars according to the Consumer Price Index (CPI). Salaries are imputed for both the position start date and the position end date. We linearly interpolate between these two values to obtain a monthly salary measure for each position. Lastly, we define a worker as foreign if the country they work in differs from the country their firm is located in.

C.3 Job titles, occupations, and task content

Job titles on LinkedIn are not standardized. For example, a software engineer may report their position as *senior software engineer*, *computer programmer*, or *sr. software eng*. To map free-text job titles into SOC codes, we use Sockit (Dixon et al., 2023), an open-source Python package. Sockit preprocesses titles by removing extraneous text (e.g., employer names or seniority titles) and normalizing word order (e.g., converting *director of nursing* to *nursing director*). It then matches cleaned titles to SOC codes, through natural language processing of O*NET's database of sample job titles. This crosswalk allows us to link each worker's non-standardized job title to standardized SOC codes. We are then able to further link these positions to O*NET's vast collection of occupation descriptors.

To characterize the task content of occupations, we follow Cortes et al. (2023), who build on Deming (2017) and Autor et al. (2003). Using the 2019 SOC codes that we assigned to each position, we construct four task intensity measures: social, cognitive, routine, and manual. The *social* task score is the average of the following four items from the O*NET skills categorization: Social Perceptiveness, Coordination, Persuasion, and Negotiation. The *cognitive* task score is the average of six items spanning O*NET skills (Mathematics, Management of Financial Resources, Management of Material Resources, Management of Personnel Resources); abilities (Mathematical Reasoning); and knowledge (Mathematics). The *routine* task score averages two items from O*NET's work context categorization: Degree of Automation and Importance of Repeating Same

[11] Employment location defaults to a user's profile location when the user does not report a location, starting in 2025, according to Revelio Labs.

Tasks. The *manual* task score is the average of two items from abilities: Multilimb Coordination and Gross Body Coordination.

Computation of these task score averages occurs as follows. We first normalize each item (within skills, abilities, knowledge, and work context) to a 0-10 scale using the observed minimum and maximum values of each across occupations. Next, we compute the average of these normalizations for each of the four task categories, and then rescale each composite to 0-10 once more. Then, we merge these occupation-level task scores to the analysis sample. We compute position-weighted percentile ranks following Minni (2024): for each task score, a worker's task percentile equals the fraction of employee-month observations in the analysis sample with task intensity at or below the worker's. The resulting measures range from 0 to 1.

We then follow Gathmann and Schönberg (2010); Minni (2024) to consider how workers change occupations and in particular change tasks, and compute the following task distance. Each occupation j is characterized by a task vector $q^j = (q^j_c, q^j_m, q^j_r, q^j_s$, where q^j_d is the task intensity for dimension $d \in \{\text{cognitive, manual, routine, social}\}$. The angular separation between occupation j and k is given by:

$$\text{Angular Separation}_{jk} = \frac{\sum_{d\in\{c,m,r,s\}} \left(q^j_d \times q^k_d\right)}{\left[\left(\sum_{d\in\{c,m,r,s\}} (q^j_d)^2\right)\left(\sum_{d\in\{c,m,r,s\}} (q^k_d)^2\right)\right]^{1/2}}. \tag{3}$$

This measures the similarity between two occupations. We then consider $1-\text{Angular Separation}_{jk}$, as a measure of the distance between two different occupations. This measure ranges from 0 to 1, where it is zero for occupations that require the same tasks and one for occupations that require completely different tasks. We consider a cumulative measure of this, which is the distance the worker changes overall each time period.

C.3.1 Definition of executive position

We define a position to be an executive position if the title contains any of the following strings: *chief executive officer*, *chief operating officer*, *chief financial officer*, *chief technology officer*, *managing director*, *executive director*, *vice president*, *president*, *ceo*, *coo*, *cfo*, *cto*, *cmo*, *cio*, *cso*, or *vp*.

C.4 Firm AKM fixed effects

To estimate the firm AKM fixed effect (Abowd et al. (1999)), we compile a sample of workers at the universe of firms ever listed in the analysis sample. For computational reasons, we cannot include the universe of observations, and so instead we randomly sample 10 workers per firm and construct a monthly worker-firm panel for each sampled worker. For each sampled worker, we

retain their full employment history, including positions at firms outside the main sample. Next, we estimate the following regression equation for each worker i in month t:

$$y_{it} = \gamma_i + \gamma_f + \gamma_t + \gamma_o + \gamma_c + \gamma_j + \gamma_h + \varepsilon_{ift} \tag{4}$$

where y_{it} is the log imputed salary for worker i at firm f in month t, γ_i are worker fixed effects, γ_f are firm fixed effects, γ_t are month fixed effects, γ_o are occupation fixed effects, γ_c are worker country fixed effects, γ_j are industry fixed effects, and γ_h are firm headquarters country fixed effects. The main estimate of the AKM fixed effect for firm f is $\hat{\gamma}_f$, which captures the firm-specific wage premium in the sample after controlling for a variety of non-firm worker and position characteristics.

D Matching procedure

Treated workers fall into one of three categories based on their labor market status prior to joining the treated firm: career starters (entering their first recorded job), unemployment-to-employment, and employment-to-employment. The main analysis focuses on employment-to-employment transitions, which comprise 75% of the sample. For each treated worker in the sample, we find a comparable control worker.

We define matching cells based on the following binned observable characteristics:[12]

- Gender
- Country of previous job
- Occupation in previous job (2-digit SOC)
- Industry in previous job (2-digit NAICS)
- Bachelor's degree completion year (6-year bins)
- Master's degree completion year (6-year bins)
- Date of transition to new firm (36-month bins)
- Duration of prior unemployment spell (4-month bins)
- Total months employed in the 24 months prior to transition (5-month bins)

Each unique vector of the above characteristics defines a matching cell. We first take each treated worker and collapse the sample into these matching cells, obtaining counts per cell. Per cell, we find an equivalent number of distinct control workers with the same set of characteristics but who are switching into a non-treated firm. We are able to match 89% of treated workers with a control worker. We verify the quality of the match with a balance table comparing treated

[12] When a matching characteristic is missing (e.g., a worker who doesn't list a degree), the missing value is treated as its own bin. Thus, treated and control workers are also matched on whether they are missing certain qualities.

and control workers on both match characteristics and non-matched characteristics. Table A7 shows the results among treated workers with a matched control worker. Characteristics that we matched at the bin level may show slight differences across treated and non-treated workers, but no economically significant differences emerge. Furthermore, the main empirical specification controls for each of these characteristics.

Table A7: Balance Test: Treated vs. Control Workers

Variable	N (treated)	Treated mean	N (control)	Control mean	Diff (p-val)
Panel A: Matched characteristics					
Male	118116	0.660	118116	0.660	0.000 (1.000)
Age	118929	28.635	118929	28.270	0.365 (0.000)
Previous job country	114061	176.453	114444	175.881	0.572 (0.100)
Previous occupation (2-digit SOC)	94110	26.829	104569	26.681	0.148 (0.018)
Bachelor's completion year	59182	2014.157	59182	2014.253	-0.097 (0.019)
Has bachelor's degree	118929	0.369	118929	0.359	0.010 (0.000)
Has graduate degree	118929	0.204	118929	0.217	-0.013 (0.000)
Panel B: Non-matched characteristics					
Pre-transition salary	94109	63778.230	104569	55574.529	8203.702 (0.000)
Founder (pre-transition)	116995	0.023	117364	0.019	0.005 (0.000)
Executive (pre-transition)	116995	0.035	117364	0.031	0.003 (0.000)

Notes: This table compares pre-event means for treated and control workers. The last column reports the difference in means and the p-value from a two-sided t-test in parentheses.

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