Understanding Workers' Migration Response to Shocks: Mass Layoffs in Brazil*

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Abstract

This paper investigates the impact of unexpected employment shocks on workers' migration decisions using matched employer-employee data from Brazil's formal sector. Leveraging an event-study design, we find that workers who separate from their firm during a mass layoff face a significant and persistent 10% decline in their earnings relative to non-laid-off workers. We also find that laid-off workers are 15 percentage points more likely to migrate to another labor market. While all laid-off workers migrate at higher rates than non-laid-off workers, we find that men migrate at higher rates than women, and that non-white workers migrate more than white workers. We explain these patterns through a descriptive exercise comparing wage trajectories of migrant and non-migrant laid-off workers. We find 1.5% higher earnings among migrants than stayers, with almost all gains concentrated among men and larger gains among non-white workers. We complement our empirical evidence with a location-choice model that delivers a gravity equation for bilateral migration flows. Gravity estimates indicate that a one-standard-deviation increase in layoff intensity raises flows out of the origin by roughly 1-3%. Taken together, the findings show that mass layoffs trigger substantial but selective geographic reallocation, and that unequal access to migration shapes the distributional consequences of employment shocks.

Keywords: Mass Layoff, Migration

JEL Classification: O15; J61; J63

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1 Introduction

The ability of workers to mitigate unfavorable labor market outcomes through migration is a key determinant of the welfare implications of shocks (Blanchard and Katz [1992]; Autor et al. [2016]). Unexpected employment shocks like mass layoffs are specifically associated large and persistent wage declines for affected workers (Jacobson et al. [1993]; Scur and Schmutte [2024]). Separation shocks also create conditions, such as congestion in labor markets, that would encourage migration as an adjustment mechanism (Foote et al. [2019]; Mercan et al. [2024]). Yet, there is limited evidence on how sudden and unanticipated separation shocks affect internal migration, which workers are able to move, and whether those who migrate are able to avoid earnings losses.

This paper aims to address this gap and investigate the causal effect of unforeseen job displacement shocks on workers' migration behavior. Our analysis proceeds in two steps. First, we use an event-study design, leveraging matched employer-employee data from Brazil's formal sector to provide estimates of the impact of mass layoff events on workers' decision to migrate. We document significant heterogeneity in migration levels across a host of worker, establishment, job, and labor market characteristics at the time of separation. The richness of our data allows us to follow workers who migrate and compare their outcomes to those who do not to describe potential motivations and constraints associated with migration decisions. Second, we complement our empirical findings by developing a location choice model to unwind the origin-push and destination-pull factors driving migration decisions in response to mass layoffs. Using our model, we derive and estimate a gravity equation to explain how layoff shocks reallocate workers across labor markets in Brazil.

Our empirical analysis yields four main findings. First, workers displaced in mass layoffs suffer persistent wage losses of around 10% relative to a sample of non-displaced workers with similar characteristics, consistent with findings in the displacement literature. Second, mass layoffs substantially increase the probability of migration: displaced workers are up to 15 percentage points (p.p.) more likely to take a job in a different microregion than comparable non-displaced workers.

Third, we find that there is pronounced heterogeneity in migration responses and in the returns to moving. Local labor market conditions appear to matter: response is stronger when the intensity of the layoff is larger or if the origin labor market is highly concentrated. Men are roughly 5 p.p. more likely to migrate after a mass layoff than women. There are also racial differences, with non-

white workers being 0.6 p.p. more likely to relocate. We also find that college-educated workers, workers with white-collar jobs, and those aged 25-44 migrate most in response to a mass layoff shock. Workers in retail and manufacturing migrate at much lower rates than workers in high-value service and construction industries.

We also explore the relationship between migration decisions and post-layoff wage trajectories. Among displaced workers, those who migrate earn on average about 1.5 percentage points more than displaced workers who stay, but these gains are concentrated among men; for women, we estimate no significant earnings advantage from migration. Non-white displaced workers who move tend to relocate to local labor markets with lower shares of people of color and higher wages, and they experience earnings gains relative to non-migrating non-white workers.

Finally, using a gravity equation derived from an occupational choice model, we show that a one-standard-deviation increase in layoff shocks in a microregion raises worker flows towards faster-growing regions by roughly 1–3%, suggesting that mass layoffs can accelerate reallocation toward higher-growth areas and that might be mediated by who is able to migrate.

Our study contributes to multiple intersecting literatures investigating job displacement and worker mobility in response to shocks, linking labor market shocks, selection into migration, and inequality in a developing-country context. We follow Jacobson et al. [1993]'s seminal work in using mass layoffs as plausibly exogenous shocks at the worker level to study workers' migration decision. Existing work on mass layoffs in Brazil has documented large and persistent earnings losses, increase in entrepreneurship, and decline in spending among laid-off workers (Dal-Ri [2024]; Scur and Schmutte [2024]; Martins-Neto et al. [2024]; Mata et al. [2023]; Corado [2023]; Van Doornik et al. [2023]; Britto et al. [2022]) but provides relatively little evidence on displaced workers' migration responses. We contribute to this literature by providing, to our knowledge, the first causal evidence linking mass layoffs to migration.

A separate but connected literature is concerned with worker mobility as a mechanism for regional adjustment in response to shocks (Autor et al. [2016]; Dix-Carneiro et al. [2018]; Foote et al. [2019]; Huttunen et al. [2018]). We add to this literature by providing individual-level evidence on how job displacement translates to migration and how that connects to post-displacement earnings trajectories. Finally, we also contribute new evidence to the literature on gender and racial heterogeneity in access to migration as a mechanism for adjustment to shocks (Bryan and Morten [2019];

Baum-Snow et al. [2018]; Diamond [2016]).

The rest of this paper is organized as follows. Section 2 describes our data and Section 3 goes over our sample selection and the creation of key variables for our analysis. Section 4 discusses our empirical strategy. Section 5 provides our empirical results. In Section 6, we build a location-choice model which yields a gravity equation. Section 7 discusses our gravity estimates and Section 8 concludes.

2 Data

The primary data source we use for this paper is an administrative matched employer-employee dataset called the *Relação Anual de Informações Sociais (RAIS)*. The data cover the universe of formal employment in Brazil and are accessed subject to a confidentiality agreement between Cornell's Labor Dynamic Institute and the Ministry of Labor in Brazil. The RAIS data contain annual information about worker and job characteristics covering the universe of formal employment in Brazil. Each observation in the dataset is at the worker-establishment-year level and details sex, age, education information about the worker, location and industry of the establishment where they are employed, and information about occupation, salary and contracts. We specifically use data between 2002 and 2017, containing over 1.1 billion observations to create a quarterly panel.

The RAIS data contain time-invariant individual "Cadastro de Pessoa Física (CPF)" identifiers which allow for tracking worker trajectories over time. The data also provide location information for a worker's job, mapped to one of Brazil's 5,569 municipalities. We map the municipalities to one of 558 microregions, which we use as commuting zones for our analysis.[1] The data also contain "Classificação Nacional de Atividades Econômicas (CNAE)" codes associated with the industry of a worker's establishment and "Código Brasileiro de Ocupações (CBO)" codes associated with a worker's role. The richness of these data enables us to estimate differences in outcomes between workers who are similar across across a broad range of observable individual-level traits.

[1] Starting in 2017, IBGE Brazil uses Immediate and Intermediate Geographic Regions as units of analyses. Since our analysis ends in 2017, we stick to the original microregion definitions. Our results are unaffected by this choice. You can read more here.

3 Sample Selection

3.1 Mass Layoff Events & Affected Workers

In order to identify a mass layoff event, we first create a quarterly employment panel at the establishment level using the annual RAIS data. We limit the analysis only to private sector establishments with 50 or more workers in both quarters $t-1$ (immediately before the event) and $t-4$ (one year before the event). We identify a mass layoff establishment as one where employment drops at least 30% between quarters $t-1$ and t and between quarters $t-4$ and t. We exclude all establishments where employment declines are associated with restructuring or M&A events to not conflate them with mass layoffs.

A mass laid-off (treated) worker is then classified as such if she is employed at an establishment that experiences a mass layoff event in quarter t and she separates from that employer in the same quarter t. We limit to cases where the worker is not re-employed at the mass layoff establishment between quarters $t+1$ and $t+12$, guaranteeing that separations are permanent. We also exclude workers without attachment to the establishment (tenure lower than 2 years), part-time workers (contracts lower than 30-hours/week) or those outside prime working-age workers (ages 20 to 50). Finally, we limit workers to their first layoff event. Fig. 1 shows a map of mass layoffs identified across all microregions of Brazil.

3.2 Matched Control Group

Since our sample selection limits the analysis to workers at a subset of large establishments in the economy, we define a matched comparison sample of non-laid-off (control) workers. We implement this in four steps. First we exclude any workers at a mass-layoff establishment along with implementing the same attachment, contract, and age restrictions as our treatment sample. Next, the non-laid off workers are categorized into cells defined by two key dimensions: two-digit industry in quarter $t-1$ and gender. The trajectory of these workers serves as the counterfactual trajectory of laid-off workers if they had not been laid off, allowing us to identify the effect of layoffs on migration decisions. Third, within each cell, we apply a one-to-one matching algorithm, ensuring that the number of non-laid-off workers matches that of laid-off workers. This matching algorithm consists of creating a cell-specific score for the propensity that a worker is laid off based on the

following observable dimensions: wages in quarters $t-8$ and $t-4$, age in quarter $t-1$ (in three groups: 20 to 29, 30 to 39, and 40 to 50), months of tenure in quarter $t-1$, employer size in quarter $t-1$ (measured by the number of employees), and educational group (measure by highest completed degree: elementary education, primary education, high school, and college). Table 1 shows summary statistics for our treated and control groups for matched and unmatched variables. Fig. 2 plots wages for the displaced and control workers preceding and following the mass layoff event and shows a visible and persistent decline in wages for the displaced.

Table 1: Descriptive Statistics: Laid-Off vs Matched Non-Laid-Off Workers

	Laid-Off			**Matched Non-Laid-Off**			
	Mean	Median	SD	Mean	Median	SD	Diff
Matching variables							
Worker: Wage in t=-8	6.92	6.82	0.59	6.93	6.83	0.59	0.01^{***}
Worker: Wage in t=-4	6.99	6.88	0.60	7.00	6.90	0.60	0.01^{***}
Worker: Age	34.73	34.00	7.98	34.66	34.00	8.02	-0.07^{***}
Worker: Months of Tenure	18.52	13.00	14.88	17.92	13.00	14.21	-0.61^{***}
Worker: Years of Education	9.77	10.00	3.35	9.84	10.00	3.30	0.07^{***}
Worker: Female	0.32	0.00	0.46	0.32	0.00	0.46	0.00
Sector: Agriculture	0.04	0.00	0.19	0.04	0.00	0.19	0.00
Sector: Manufacturing/Mining	0.37	0.00	0.48	0.37	0.00	0.48	0.00
Sector: Construction	0.14	0.00	0.34	0.13	0.00	0.34	0.00^{***}
Sector: Retail	0.07	0.00	0.26	0.07	0.00	0.26	0.00
Sector: Services	0.38	0.00	0.49	0.39	0.00	0.49	0.00^{*}
Other variables							
Worker: White	0.51	1.00	0.50	0.57	1.00	0.49	0.06^{***}
Occupation: Manager	0.02	0.00	0.12	0.02	0.00	0.13	0.00^{***}
Occupation: WC professional	0.10	0.00	0.30	0.10	0.00	0.30	0.00
Occupation: BC Worker	0.87	1.00	0.33	0.87	1.00	0.34	-0.01^{***}
Region: North	0.07	0.00	0.26	0.04	0.00	0.19	-0.03^{***}
Region: Northeast	0.19	0.00	0.39	0.16	0.00	0.37	-0.02^{***}
Region: Southeast	0.53	1.00	0.50	0.55	1.00	0.50	0.02^{***}
Region: South	0.13	0.00	0.34	0.18	0.00	0.39	0.05^{***}
Region: Center-West	0.08	0.00	0.27	0.07	0.00	0.25	-0.01^{***}
Observations	719.270			719.270			

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

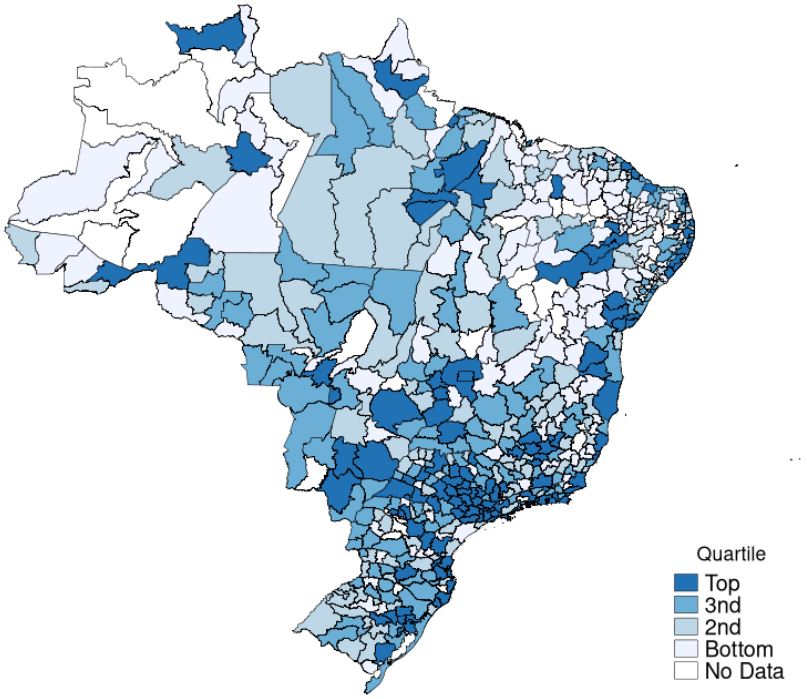


Figure 1: Mass Layoffs identified across the country; concentrated in population centers

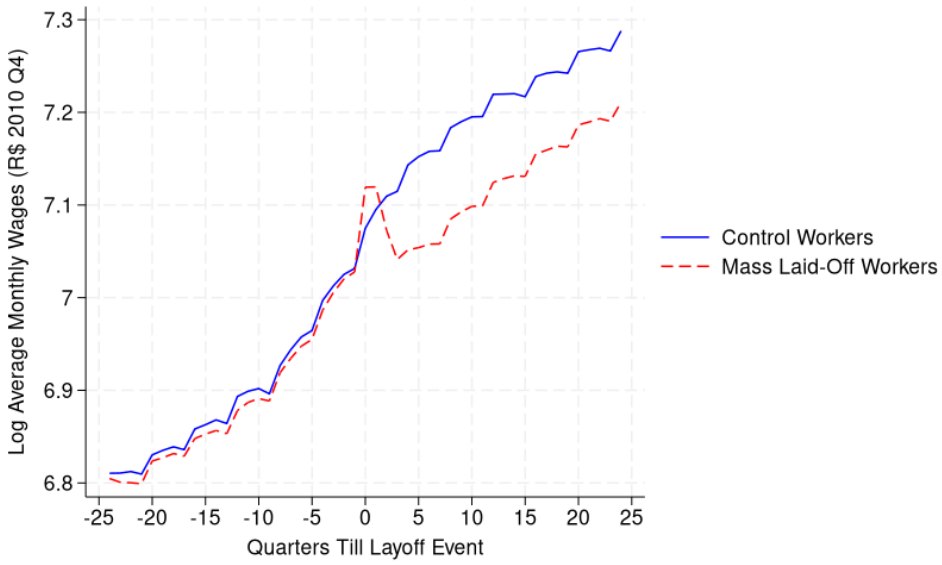


Figure 2: Displaced workers face a sustained loss in wages

3.3 Identifying Migration

In the RAIS data, we can observe the location of a worker's job at the municipality level and use it to ascertain her migration status. We create extensive-margin migration indicators $Y_{it} \in \{0, 1\}$, where a value of one indicates that the worker is observed in a different microregion/state than the one they were in quarter $t-1$. We also create an intensive-margin migration distance variable by calculating the kilometer straight-line distance between the centroids of the two municipalities between which workers are moving.

After separating from their previous employer during a mass layoff event, Over 85% of affected workers return to formal employment within the next 12 quarters and their migration status can therefore be documented in the RAIS. As a conservative measure, we assume workers have not migrated in quarters where we don't observe them in the RAIS but our results are stronger in the same direction if we exclude these workers (see appendix).

4 Empirical Strategy

We estimate the impact of a mass-layoff event on a change in the probability of the worker migrating to a different microregion using an event study design with a regression of the form:

$$Y_{it} = \sum_{k \neq -1} \beta_k \mathbb{1}\{K_{it} = k, Treated_i = 1\} + \alpha_i + \lambda_t + \theta_{K_{it}} + \varepsilon_{it}, \tag{1}$$

where $\mathbb{1}\{K_{it} = k\}$ are mutually exclusive lead/lag dummies relative to the layoff ($k = -1$ omitted), α_i are worker fixed effects absorbing all time-invariant heterogeneity, λ_t are quarter fixed effects absorbing aggregate shocks, and $\theta_{K_{it}}$ are relative-time fixed effects absorbing movements that are common to treated and matched controls at a given relative quarter, absorbing any generic dynamics around the event clock that are shared by treated and matched controls. The coefficients $\{\beta_k\}$ trace the dynamic treatment path for treated workers relative to matched controls, with β_{-q} $(q \geq 2)$ serving as pretrend diagnostics and $\beta_0, \beta_1, \ldots, \beta_n$ the post-event effects of interest. For binary outcomes we estimate (1) using a linear probability model with high-dimensional fixed effects, with standard errors clustered at the local labor market (microregion x industry) level.

Identification here is dependent on the canonical parallel trends assumption which states that

in the absence of the mass layoff event, the migration probabilities of control and treated workers would have moved similarly. This is a reasonable assumption in this setting as these workers share several observable characteristics and similar pretrends.

5 Empirical Results

5.1 Mass Layoffs & Wages

Fig. 3 shows that wages for workers displaced during a mass layoff are 8-10% lower at their next job as documented widely in the literature. These lower wages persist for several periods.

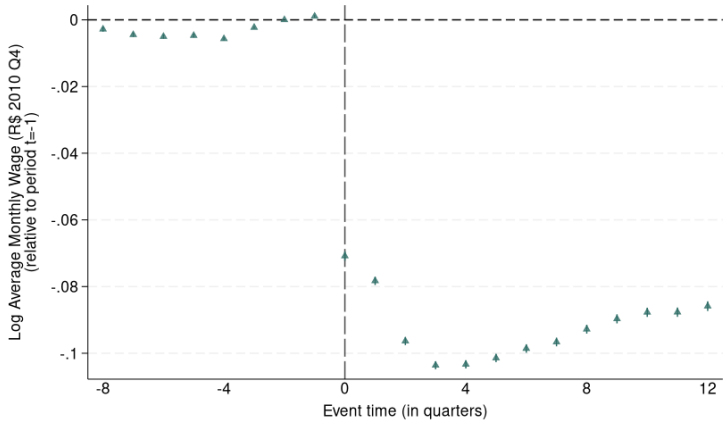


Figure 3: Mass Layoff Impact on Wages in Subsequent Quarters

5.2 Migration Response

Fig. 4 documents a sizable 10-15 p.p. effect of mass layoffs on workers' decision to relocate as a result of being displaced from their job during a mass layoff when compared to a control worker. The effect is immediate and sustained, peaking around one year after the layoff event. This large effect could be indicative of the fact that that losing their job reduces the cost of migration for workers. This finding is robust to alternative definitions of migration.[2]

[2]Results for an alternative intensive migration measure (interstate migration) and an extensive migration measure (migration distance) are provided in the appendix.

5.3 Heterogeneity

While workers who separate from their employer during a mass layoff consistently migrate at higher rates than control workers, there is wide heterogeneity in the level of migration across a range of observable worker, job, establishment, and labor market characteristics. We estimate this by running our analysis interacted with heterogeneous characteristics associated with the worker at the time of separation.

5.3.1 Worker Characteristics

Fig. 5 shows that men are up to 5 p.p. more likely to migrate to a new microregion for their next role than women. Fig. 6 shows that non-white workers are on average 0.6 p.p. more likely to migrate to a new microregion for their next role than white workers. We discuss possible reasons for these trends later in Section 5.5.

Fig. 7 shows that while there is far less migration variability among displaced workers by age, young and old workers migrate less than those in the prime working age between 25-45. Fig. 8 shows us that at least initially, college-educated displaced workers migrate more than workers with lower levels of education, though over time the levels become more comparable. Additionally, Fig. 9 shows that white-collar professionals and blue-collar technicians are more likely to move than managers and non-clerical blue-collar workers.

5.3.2 Industry of Establishment

Next, we identify the industry of the establishment from which a treated worker separates during a mass-layoff and interact it with our event study estimation, comparing treated and control workers of the same industry. We find that workers employed in retail or heavy industry work at the time of separation migrate to a new microregion at a much lower rate than workers in construction, agriculture, or modern services. These findings are displayed in Fig. 10. A summary of migration estimates among displaced workers four quarters after a mass layoff is provided in Table 2

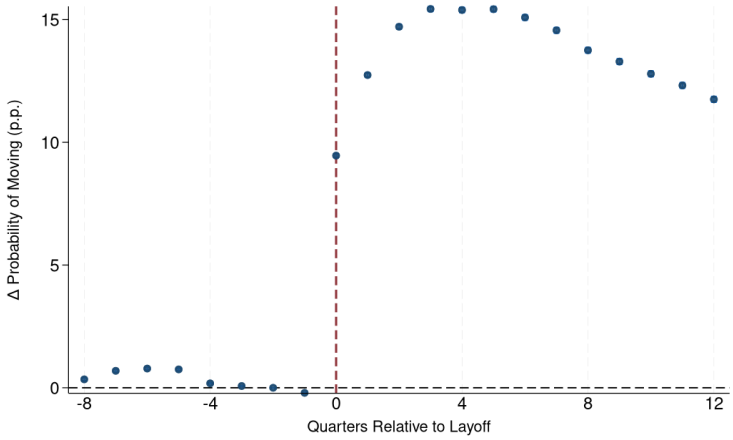


Figure 4: Mass Layoff Impact on Migration out of Microregion

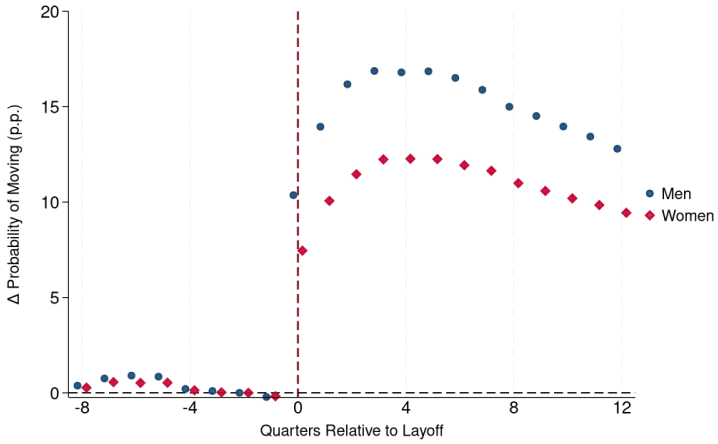


Figure 5: Men migrate at higher rates than women

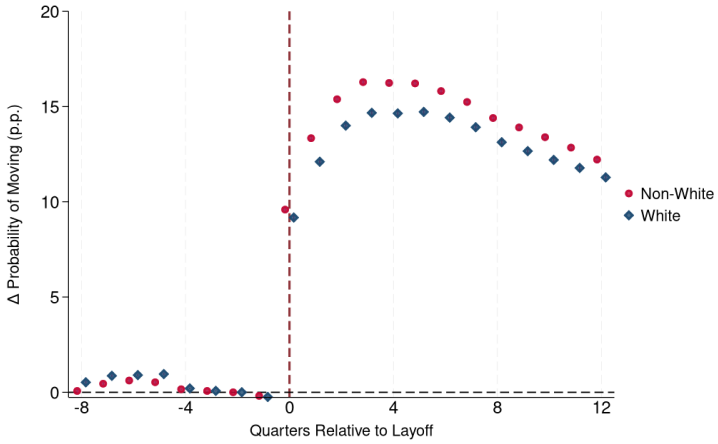


Figure 6: Non-white workers migrate at higher rates than white workers

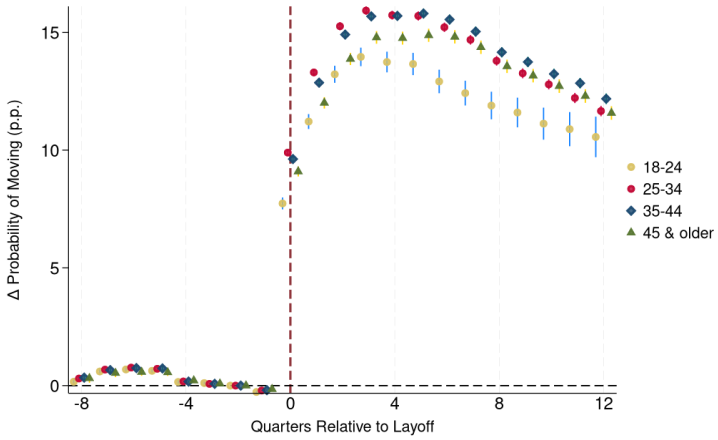


Figure 7: Prime age workers most likely to migrate

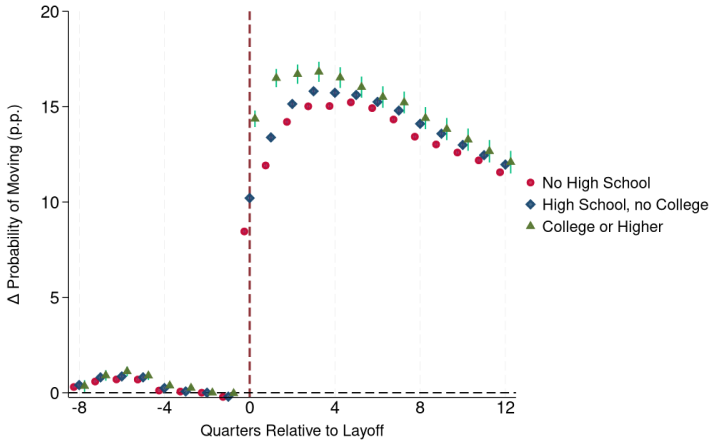


Figure 8: College educated workers migrate more

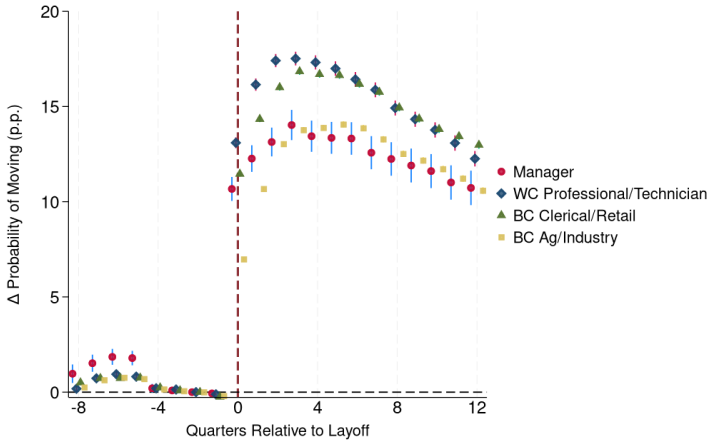


Figure 9: White-collar professionals and Blue-collar clerical workers migrate more

5.4 The Role of Labor Market Conditions

5.4.1 Treatment Intensity

To assess whether migration responses vary with the local severity of the shock, we define a baseline local labor market level intensity measure as the share of workers in worker i's origin local labor market[3] affected by mass layoffs at time $k = -1$. We discretize intensity into three bins; $< 1\%$, 1–10%, $> 10\%$ and interact event-time dummies with these bins.

As shown in Fig. 11, we find that local labor markets facing more intense mass layoff shocks show much higher rates of out-migration. This could suggest that workers migrate away at higher rates as congestion in local labor markets rises and reduces their probability of finding a job.

5.4.2 Local Labor Market Concentration

Another potential reason why migration might be an important tool for workers post-layoff would be to escape highly concentrated local labor markets with potentially larger markdowns. To assess whether migration responses to mass layoffs vary by concentration levels in a worker's local labor market, we calculate employment and payroll HHIs for all markets in each quarter as follows:

Let c index local labor markets, t quarters, and f firms. For each triplet (c, j, t). Denote by E_{fct} the number of formal employees of firm f in local labor market c in quarter t. Total employment in that cell is $E_{ct} = \sum_f E_{fct}$. The employment share of firm f in (c, t) is thus $s^E_{fct} = 100 \times \frac{E_{fct}}{E_{ct}}$. The employment-based HHI is then given by $\text{HHI}^E_{ct} = \sum_f \left(s^E_{fct}\right)^2$ so that a value of 10,000 corresponds to a local monopoly and lower values indicate less concentration.[4]

For the heterogeneity analysis, we interact the concentration level of a worker's labor market at the time of separation with their migration status in our event study set-up. Specifically, we compare workers in highly concentrated local labor markets with HHI above 2500 against workers in unconcentrated markets with HHI below 1200. As shown in Fig.12, we find that workers facing a layoff shock in more concentrated labor markets migrate away at higher rates.

[3] Defined as microregion x 2-digit-industry

[4] Analogous calculation is done to obtain a payroll-HHI based on share of total wages paid by each firm. Results do not change depending on which measure is used.

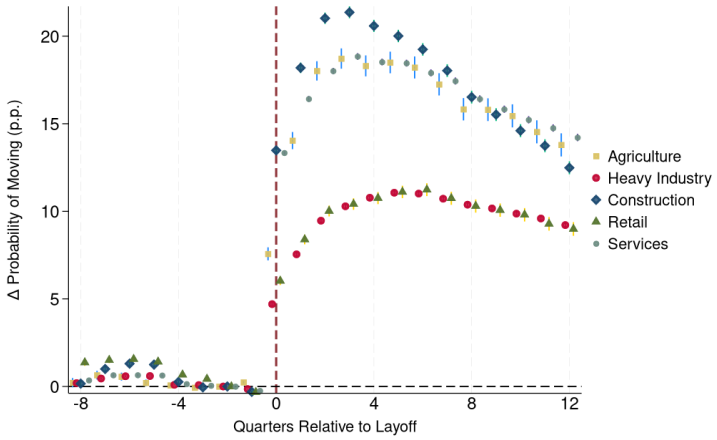


Figure 10: Manufacturing & retail workers migrate far less than workers in other industries

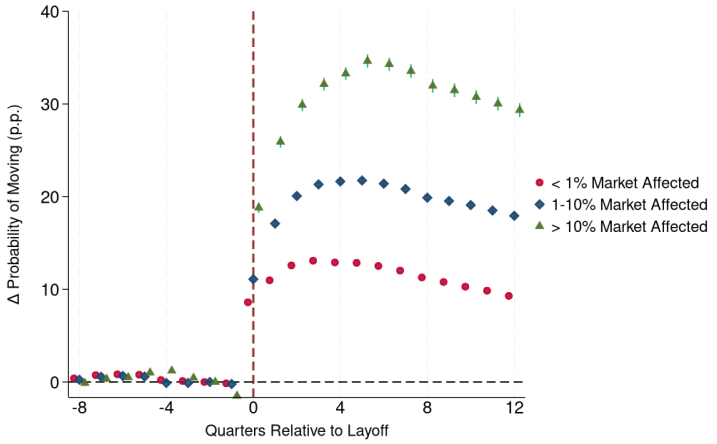


Figure 11: Workers in more intensely treated LLMs migrate more

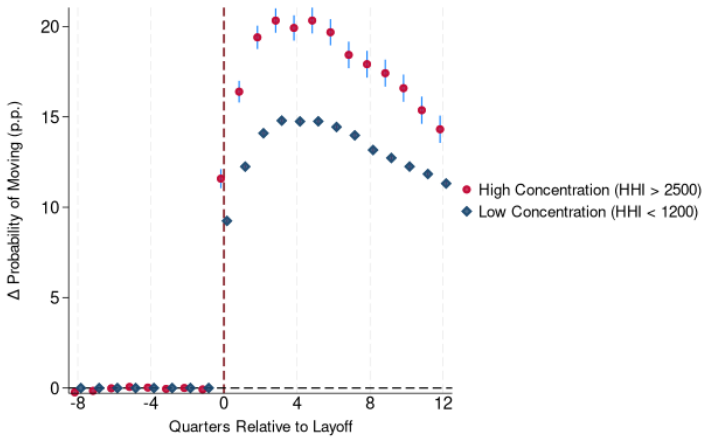


Figure 12: Workers in more concentrated LLMs migrate more

5.5 Gains from Migration

Our analysis thus far has demonstrated the causal impact of mass layoffs on migration. As a next step in understanding a worker's migration decision, we switch to using our event study for descriptive analyses documenting the trajectories of the workers within our sample.

First, we begin by comparing treated workers who migrate and who don't against control workers with the same migration status. This analysis is descriptive because we do not claim that the control workers who would make the choice to migrate without facing a shock are the same as the workers who would choose to stay. Yet what we find in Fig. 13 is interesting as we see that while all displaced workers face lower wages, migrants have higher wages on average than stayers when compared to control workers.

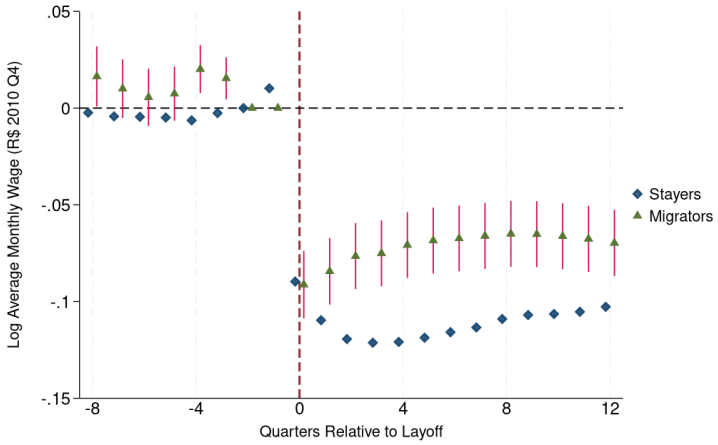


Figure 13: Migrants out-earn stayers compared to control workers

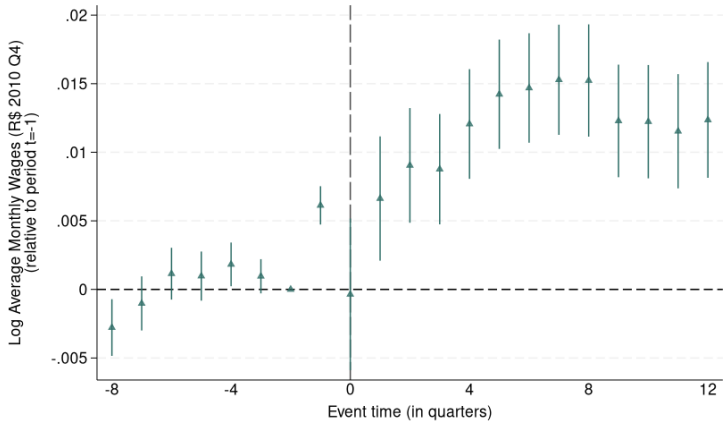


Figure 14: Comparing within displaced workers, migrants out-earn stayers

We take this comparison one step further by comparing only displaced workers against each other in a novel event study based on whether they migrate or not. We re-run the same matching algorithm we used originally to match displaced migrant and non-migrant workers on observables. We obtain over 217,000 matches whose trajectories we compare. Primarily, as shown in Fig. 14 we find that among displaced workers, migrants out-earn stayers by up to 1.5% after 2 years.

We see evidence for the fact that these gains from migration are not even across all migrants. Fig. 15 shows that almost all the gains in earnings from migration are concentrated among men. This could partially help explain why men migrate at higher rates than women. Additionally, Fig. 16 shows that non-white workers gain more from migration. This could be driven by non-white workers being separated away from opportunity and having to relocate to growing regions.

Table 2: Event Study Results - Prob. of Moving to Another Microregion $t+4$ Quarters after Event

Base, Gender & Race

	(1) All	(2) Men	(3) Women	(4) Non-White	(5) White
Δ Prob. of Moving MR	0.1539***	0.1680***	0.1227***	0.1624***	0.1464***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Observations	32,316,102	22,254,204	10,061,898	13,233,507	17,753,022

Education Level

	(1) No HS	(2) HS, no College	(3) College+
Δ Prob. of Moving MR	0.1503***	0.1573***	0.1653***
	(0.001)	(0.001)	(0.003)
Observations	17,292,534	13,536,138	1,487,430

Age Group

	(1) 18-24	(2) 25-34	(3) 35-44	(4) 45+
Δ Prob. of Moving MR	0.1374***	0.1573***	0.1570***	0.1476***
	(0.002)	(0.001)	(0.001)	(0.001)
Observations	2,763,735	12,788,992	11,146,250	5,617,125

Occupation at Treatment

	(1) Manager	(2) WC Prof/Tech	(3) BC Cler/Retail	(4) BC Ag/Ind
Δ Prob. of Moving MR	0.1344***	0.1732***	0.1670***	0.1389***
	(0.004)	(0.002)	(0.001)	(0.001)
Observations	575,043	3,192,840	12,465,075	15,517,026

Industry at Treatment

	(1) Agriculture	(2) Heavy Ind.	(3) Construction	(4) Retail	(5) Services
Δ Prob. of Moving MR	0.1830***	0.1078***	0.2058***	0.1075***	0.1852***
	(0.003)	(0.001)	(0.002)	(0.002)	(0.001)
Observations	1,164,198	11,704,518	4,378,626	2,489,130	12,579,630

Notes: Entries report the coefficient on the event dummy at $t+4$ quarters after mass layoff. Standard errors in parentheses, clustered at the individual level.

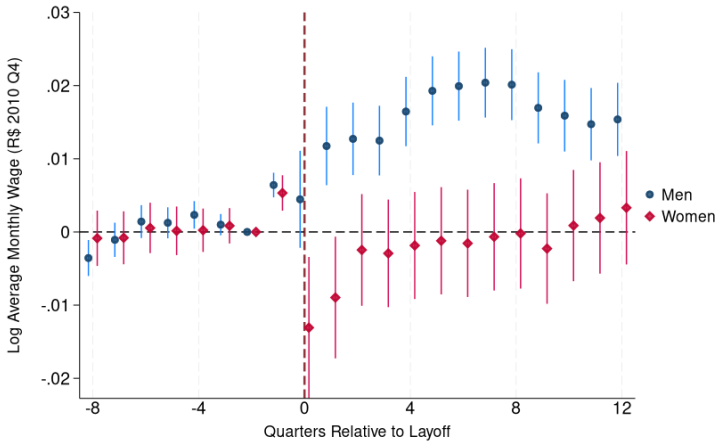


Figure 15: Benefits from migration concentrated among men

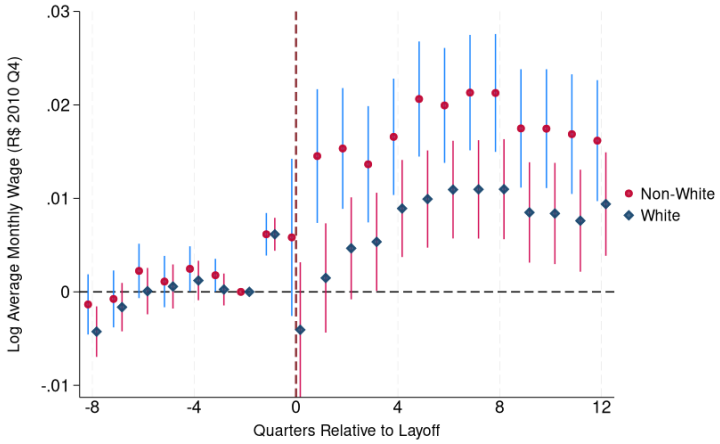


Figure 16: Non-white workers gain more from migration

6 Conceptual Framework (Preliminary)

In this section, we outline a simple location–choice model with mobility costs that provides a micro-foundation for a gravity equation for bilateral migration flows. Mass layoffs enter into the model by lowering the value of staying in the origin for a worker. This could be driven by congestion in the local labor market post-layoff that reduces the probability of finding a job and expected wages.

6.1 A Static Location Choice Problem with Mobility Costs

Consider a set of locations $\mathcal{J}$ (micro-regions). In each period t, a worker who currently resides in origin $i \in \mathcal{J}$ chooses a destination $j \in \mathcal{J}$ at which to live and work.[5]

Let the (indirect) utility of a worker from i choosing destination j in period t be

$$U_{ijt} = v_{jt} - \kappa C_{ij} - \chi \cdot \mathbf{1}\{j \neq i\} + \theta \mathrm{LI}_{it} \cdot \mathbf{1}\{j = i\} + \varepsilon_{ijt}, \tag{2}$$

where

- v_{jt} collects destination-time characteristics that affect utility (expected wages, amenities, job-finding probability, etc.);
- C_{ij} is a bilateral, time-invariant mobility cost between i and j (distance, cultural barriers, lack of networks, etc.);
- $\kappa > 0$ scales the disutility of mobility costs, and $\chi \geq 0$ captures a fixed cost of moving away from i;
- LI_{it} is a measure of layoff intensity in origin i at time t; for $j = i$ a higher LI_{it} reduces the value of staying, so we expect $\theta < 0$; It is measured as $\mathrm{LI}_{it} = 1000 \times \frac{\mathrm{treated}_{it}}{\mathrm{emp}_{it}}$ (per 1,000 workers).
- ε_{ijt} is an idiosyncratic taste shock, assumed i.i.d. Type-1 extreme value across j.

For intuition, one can think of v_{jt} as a reduced-form index of destination attractiveness,

$$v_{jt} = \beta_w w_{jt} + \beta_a A_{jt} + \beta_g G_{jt} + \eta_j, \tag{3}$$

[5] In the baseline formulation, "origin" i is the location of the worker's last job; in the flow data M_{ijt} denotes moves from i to j between two quarters.

where w_{jt} is an expected wage, A_{jt} is an amenity term, G_{jt} is a destination-time demand shifter (e.g. a shift-share "growth exposure"), and η_j is a time-invariant destination fixed effect.

Mass layoffs at origin i operate through LI_{it}: a higher layoff intensity lowers the utility of staying in i (the $j = i$ alternative) through a lower expected wage and/or higher unemployment risk, thereby raising the relative attractiveness of moving to $j \neq i$.

6.2 Choice Probabilities and Gravity-style Migration Flows

With the logit assumption on ε_{ijt}, the probability that a worker currently at i chooses destination j is

$$P_{ijt} = \Pr\{U_{ijt} \geq U_{ikt} \ \forall k\} = \frac{\exp\left(V_{ijt}\right)}{\sum_{k \in \mathcal{J}} \exp\left(V_{ikt}\right)}, \tag{4}$$

where the deterministic component is

$$V_{ijt} = v_{jt} - \kappa C_{ij} - \chi \, \mathbf{1}\{j \neq i\} + \theta \mathrm{LI}_{it} \cdot \mathbf{1}\{j = i\}. \tag{5}$$

Let N_{it} denote the number of potential movers currently attached to origin i in period t (e.g. the relevant formal workforce). The expected number of migrants from i to j between t and $t+1$ is then

$$M_{ijt} = N_{it} P_{ijt} = N_{it} \frac{\exp\left(V_{ijt}\right)}{\sum_{k \in \mathcal{J}} \exp\left(V_{ikt}\right)}. \tag{6}$$

Equation (6) has a gravity flavor: flows are proportional to "mass" at the origin (N_{it}), increasing in destination attractiveness v_{jt}, and decreasing in bilateral costs C_{ij}.

Taking logs,

$$\ln M_{ijt} = \ln N_{it} + V_{ijt} - \ln\left(\sum_{k \in \mathcal{J}} \exp\left(V_{ikt}\right)\right). \tag{7}$$

The last term is the origin-specific multilateral resistance term. It is common across all destinations j for a given origin i and period t.

6.3 Connecting the Model to a PPML Gravity Regression

We now map the implied gravity equation into Poisson Pseudo-Maximum Likelihood (PPML) specifications estimated using the RAIS data.

To obtain an estimable gravity equation, we parameterize V_{ijt} linearly in observable shifters and decompose the origin and destination terms into fixed effects:

$$V_{ijt} = \alpha_{ij} + \alpha_{it} + \alpha_{jt} + \beta_{\text{LI}}\text{LI}_{it} + +\beta_{\text{rel}}\,\text{Shock}^{\text{rel}}_{ijt} + \beta_{\text{INT}}\text{LI}_{it} \times Z_{j0} + \varepsilon^{V}_{ijt}, \tag{8}$$

where

- α_{ij} is a *pair fixed effect*, capturing time-invariant bilateral mobility costs C_{ij} and any other stable bilateral affinity;
- α_{it} is an *origin×time fixed effect*, absorbing $\ln N_{it}$, the origin-specific inclusive-value term from (7), and other origin-time conditions;
- α_{jt} is a *destination×time fixed effect*, proxying v_{jt} (wages, amenities, demand conditions);
- $\text{Shock}^{\text{rel}}_{ijt}$ is a relative destination vs origin shift-share, "Bartik"-style demand shock constructed from pre-period industry shares and national sectoral growth which highlights whether one microregion is growing faster than another. For each region, the object is measured as:

$$\text{Shock}_{jt} - \text{Shock}_{it}, \quad \text{where } \text{Shock}_{it} = \sum_{s} w_{is,t_0}\, g_{st}, \quad w_{is,t_0} = \frac{\text{emp}_{is}\ \text{(pre-period)}}{\sum_s \text{emp}_{is}}, \quad g_{st} = \Delta \log(\text{emp}_s)$$

- Z_{j0} is a pre-period destination characteristic (industry mix, ethnic composition, absorptive capacity, etc.), and $\text{LI}_{it} \times Z_{j0}$ captures how layoff shocks at the origin interact with destination traits in reallocating flows across j. It will be measured as:

$$\text{Cap}_{jt} = \sum_{s} w_{js,t_0}\ \max(g_{st}, 0),$$

- ε^{V}_{ijt} is an unobserved residual component.

Substituting (8) into (6), the conditional expectation of flows takes the exponential-mean form

$$\mathbb{E}[M_{ijt} \mid X] = \exp\Big(\alpha_{ij} + \alpha_{it} + \alpha_{jt} + \beta_{\text{LI}}\text{LI}_{it} + \beta_{\text{rel}}\,\text{Shock}^{\text{rel}}_{ijt} + \beta_{\text{INT}}\text{LI}_{it} \times Z_{j0}\Big), \tag{9}$$

which is exactly the conditional mean specification estimated in the empirical work using PPML with high-dimensional fixed effects.

In particular:

- The *baseline gravity regressions* correspond to imposing α_{ij} and (common) time fixed effects τ_t, and estimating

$$\mathbb{E}[M_{ijt} \mid X] = \exp\big(\alpha_{ij} + \tau_t + \beta_{\text{LI}}\text{LI}_{it} + +\beta_{\text{rel}}\,\text{Shock}^{\text{rel}}_{ijt}\big).$$

- The *BDK-style specifications* are inspired by Borusyak et al. [2022]'s work and absorb α_{ij}, α_{it}, and α_{jt}, estimating only interaction terms of the form

$$\mathbb{E}[M_{ijt} \mid X] = \exp\big(\alpha_{ij} + \alpha_{it} + \alpha_{jt} + \beta_{\text{INT}}\text{LI}_{it} \times Z_{j0}\big).$$

  In this case, *main effects* of LI_{it} and Z_{j0} are not separately identified because they are collinear with the origin×time and destination×time fixed effects. These specifications take origin- and destination-time effects into account to avoid issues plaguing common gravity regressions.

PPML is a convenient estimator because it is consistent for (9) under weak assumptions, handles zero flows naturally, and accommodates the large set of fixed effects present in (9).

Taken together, the conceptual framework clarifies that the empirical PPML gravity specifications are not purely reduced-form regressions, but can be viewed as estimating the migration responses implied by a simple utility-based model of location choice with mobility costs and layoff-induced shocks to local labor market conditions.

7 Model Results

Results from our PPML gravity estimation can be found in Tables 3 & 4. All dependent variables are standardized. Table 3 shows the results from our first specification where we find that

a one–s.d. increase in origin layoff intensity raises expected flows from i to j by 1.3-3.3%, holding fixed bilateral costs and time effects. Table 4 shows the results from our second specification with origin- and destination-time effects, with mass layoff shock intensity interacted with a shift-share destination absorption capacity. Here we find that a one–s.d. increase in layoff intensity at i and a one–s.d. higher destination absorption capacity increases expected flows by 0.5-0.7%, conditional on orig×time and dest×time FEs. These results are indicative of the fact that mass layoff shocks reallocate workers towards local labor markets with higher growth.

Table 3: Baseline Gravity Results

	(1) (q-to-q Flows)	(2) (3-yr Window)
Origin layoff intensity (1 s.d.)	0.013*** (0.004)	0.033*** (0.003)
Destination layoff intensity (1 s.d.)	-0.002 (0.005)	-0.024*** (0.004)
Relative National Growth Exposure (1 s.d.)	0.009* (0.005)	0.008 (0.007)
Observations	5,757,726	7,230,717
Pseudo R^2	0.918	0.944

Estimator: PPML with pair and quarter FEs; SEs clustered by origin.
Coefficients are semi-elasticities under log link (approx. % change).

Table 4: BDK-style Gravity Results

	(1) (q-to-q Flows)	(2) (3-yr Window)
Orig layoff intensity X Dest Capacity (1 s.d.)	0.005 (0.007)	0.007** (0.003)
Observations	5,757,726	7,230,424
Pseudo R^2	0.918	0.952

Estimator: PPML with origin×time, destination×time, and pair FEs; SEs clustered by origin.
Coefficients are semi-elasticities under log link (approx. % change).

8 Conclusion

In this paper, we have examined how workers in Brazil adjust to unforeseen job displacement shocks and to what extent they use migration to offset poor labor market outcomes. Using mass layoffs as plausibly exogenous separation shocks and matched employer-employee data from the formal sector, we provide causal event-study estimates of migration in response to displacement shocks. We complement our empirical exercise with a simple location-choice model with mobility costs that yields a gravity equation for bilateral migration flows. We estimate this equation to interpret the patterns of reallocation structurally.

The empirical analysis leads to four main conclusions. First, workers displaced in mass layoffs experience large and persistent earnings losses of roughly 10% relative to matched controls, confirming that displacement is highly costly in this setting. Second, mass layoffs substantially raise the probability of internal migration: displaced workers are 10-15 percentage points more likely to take a job in a different microregion, with larger responses when the local shock is more intense or the origin labor market is highly concentrated. These results highlight that separation shocks trigger not only within-market adjustment but also sizeable geographic reallocation. Third, both access to migration and the returns to moving are strongly heterogeneous. Men, prime-age workers, college-educated workers, white-collar professionals, and workers in high-value services and construction are more likely to migrate, while retail and manufacturing workers move much less. Among displaced workers, migrants earn on average about 1.5 percentage points more than stayers two years after the layoff, but these gains are concentrated among men. Non-white displaced workers are somewhat more likely to migrate, and those who move tend to relocate to faster-growing, higher-wage regions with lower shares of people of color and obtain larger earnings gains than non-migrating non-white workers.

Finally, the gravity estimations based on the location-choice model show that mass layoff shocks tilt worker flows toward higher-growth destinations. A one-standard-deviation increase in layoff intensity in an origin microregion raises expected flows by roughly 1-3%, and interactions with pre-period destination absorption capacity indicate that shocks reallocate workers disproportionately toward regions with stronger growth prospects. Taken together, these findings suggest that migration is an important but selective adjustment margin: workers with lower mobility costs and

better outside options are better able to respond to worsening conditions by moving, while others remain in depressed local labor markets and bear larger long-run losses.

These results have two main implications. First, analyses of displacement that abstract from internal migration are likely to miss an important channel of adjustment and to misstate who ultimately absorbs the costs of shocks. Second, policies that relax mobility constraints may attenuate the unequal incidence of displacement costs and influence where displaced workers resettle. Future work could extend the analysis to incorporate household decisions and informal employment more explicitly, study how local insurance mechanisms and networks interact with displacement-induced migration, and examine the long-run consequences of repeated shocks and cumulative moves over the life cycle.

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A Appendix A: Defining Migration at State-Level

A.1 Migration Response

Fig. 17 documents a sizable 4.5-7 p.p. effect of mass layoffs on workers' decision to relocate as a result of being displaced from their job during a mass layoff when compared to a control worker. The effect is immediate and sustained, peaking around one year after the layoff event. A large effect at migration across states reinforces our results at the microregion level.

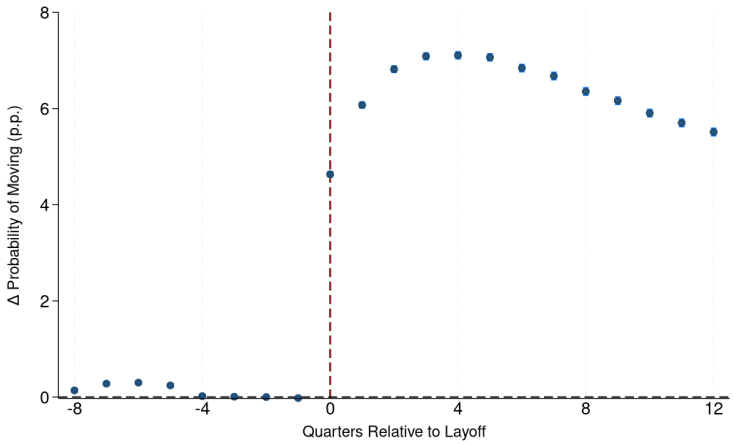


Figure 17: Mass Layoff Impact on Migration out of State

A.2 Heterogeneity

While workers who separate from their employer during a mass layoff consistently migrate at higher rates than control workers, there is wide heterogeneity in the level of migration across a range of observable worker, job, establishment, and labor market characteristics. We estimate this by running our analysis interacted with heterogeneous characteristics associated with the worker at the time of separation.

A.2.1 Worker Characteristics

Fig. 18 shows that men are up to 1 p.p. more likely to migrate to a new state for their next role than women. Fig. 19 shows that non-white workers are on average 3 p.p. more likely to migrate to a new state for their next role than white workers.

Fig. 20 shows that while there is far less migration variability among displaced workers by age, young and old workers migrate less than those in the prime working age between 25-35. Fig. 21 shows us that college-educated displaced workers migrate more than workers with lower levels of education. Additionally, Fig. 22 shows that white-collar professionals are more likely to move than all other workers. All these findings reaffirm our findings at the microregion level.

A.2.2 Industry of Establishment

Next, we identify the industry of the establishment from which a treated worker separates during a mass-layoff and interact it with our event study estimation, comparing treated and control workers of the same industry. We find that workers employed in retail or heavy industry work at the time

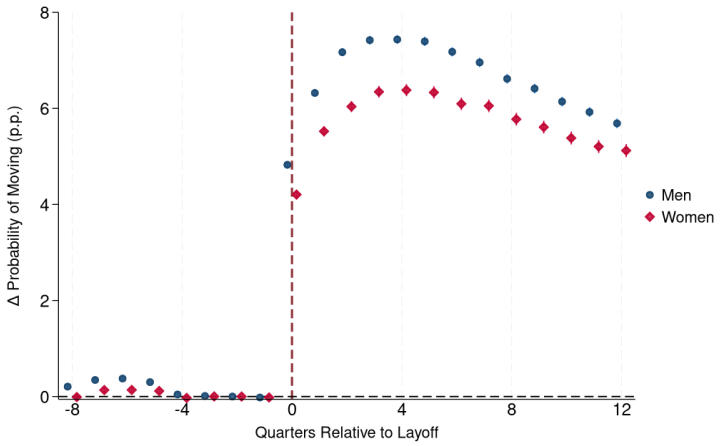


Figure 18: Men migrate at higher rates than women

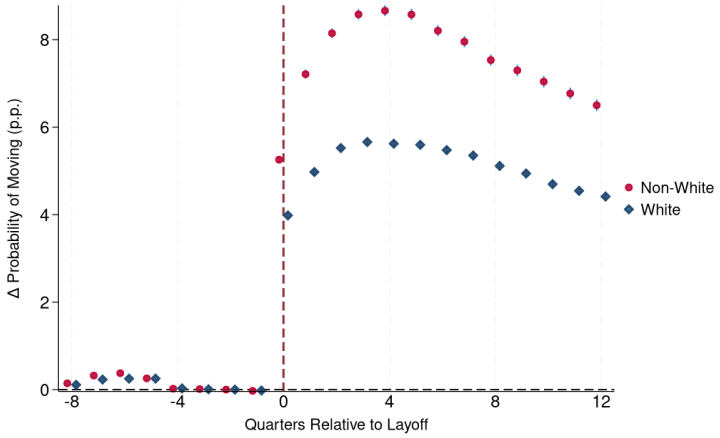


Figure 19: Non-white workers migrate at higher rates than white workers

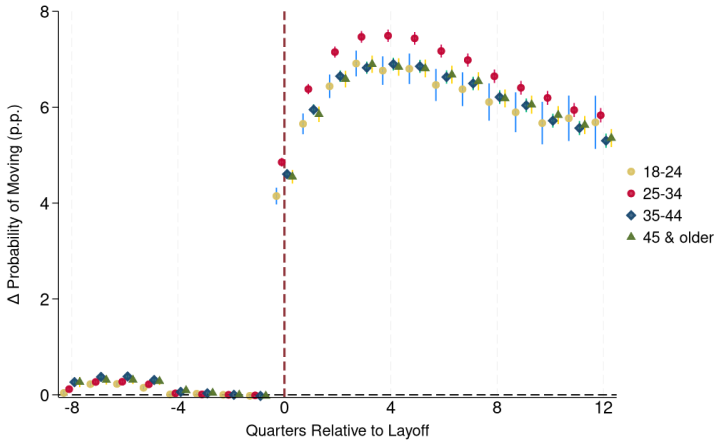


Figure 20: Prime age workers most likely to migrate

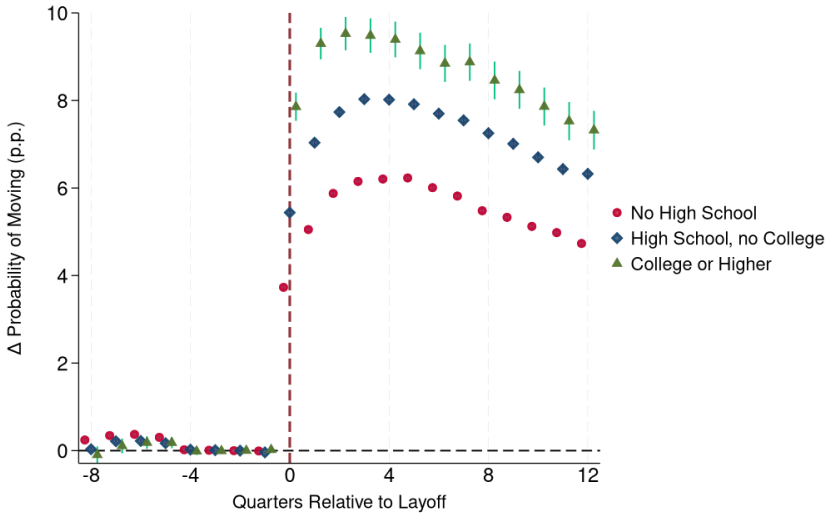


Figure 21: College educated workers migrate more

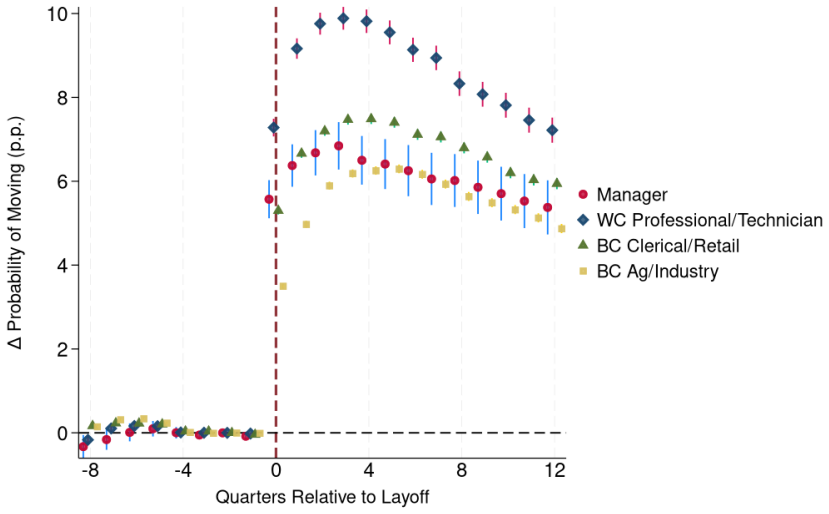


Figure 22: White-collar professionals migrate most

of separation migrate to a new state at a much lower rate than workers in construction, agriculture, or modern services. These findings are displayed in Fig. 23. A summary of migration estimates among displaced workers four quarters after a mass layoff is provided in Table 5

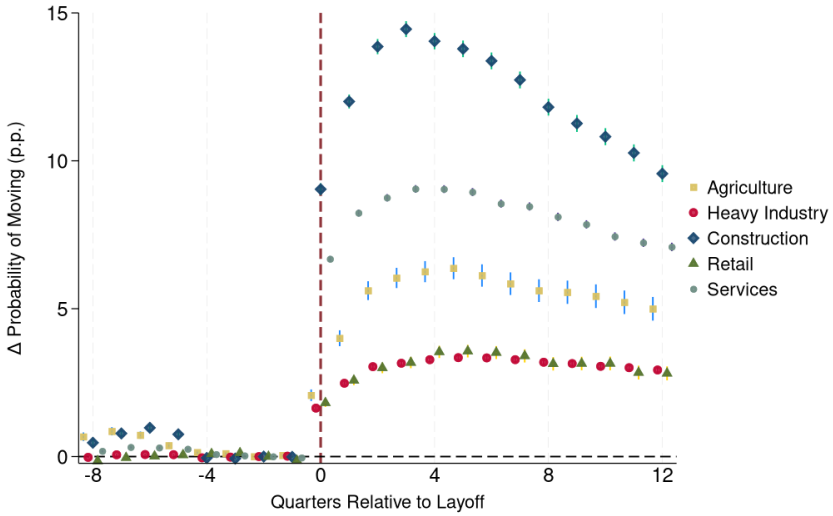


Figure 23: Manufacturing & retail workers migrate far less than workers in other industries

Table 5: Event Study Results - Probability of Moving to Another State $t+4$ Quarters after Event

Base, Gender & Race

	(1) All	(2) Men	(3) Women	(4) Non-White	(5) White
Δ Prob. of Moving to Another State	0.0711***	0.0744***	0.0638***	0.0866***	0.0562***
	(0.000)	(0.000)	(0.001)	(0.001)	(0.000)
Observations	32,316,102	22,254,204	10,061,898	13,233,507	17,753,022

Education Level

	(1) No HS	(2) HS, no College	(3) College+
Δ Prob. of Moving to Another State	0.0621***	0.0802***	0.0939***
	(0.000)	(0.001)	(0.002)
Observations	17,292,534	13,536,138	1,487,430

Age Group

	(1) 18-24	(2) 25-34	(3) 35-44	(4) 45+
Δ Prob. of Moving to Another State	0.0676***	0.0749***	0.0690***	0.0684***
	(0.002)	(0.001)	(0.001)	(0.001)
Observations	2,763,735	12,788,992	11,146,250	5,617,125

Occupation at Treatment

	(1) Manager	(2) WC Prof/Tech	(3) BC Cler/Retail	(4) BC Ag/Ind
Δ Prob. of Moving to Another State	0.0650***	0.0982***	0.0749***	0.0626***
	(0.003)	(0.001)	(0.001)	(0.001)
Observations	575,043	3,192,840	12,465,075	15,517,026

Industry at Treatment

	(1) Agriculture	(2) Heavy Ind.	(3) Construction	(4) Retail	(5) Services
Δ Prob. of Moving to Another State	0.0625***	0.0328***	0.1404***	0.0354***	0.0904***
	(0.002)	(0.000)	(0.001)	(0.001)	(0.001)
Observations	1,164,198	11,704,518	4,378,626	2,489,130	12,579,630

Notes: Entries report the coefficient on the event dummy at $t+4$ quarters after mass layoff. Standard errors in parentheses, clustered at the individual level.

B Appendix B: Migration Distance

B.1 Migration Response

Including workers who don't move at all, Fig. 24 documents a sizable 50-80 km difference in average migration distance among workers displaced from their job during a mass layoff when compared to a control worker. The effect is immediate and sustained, peaking around one year after the layoff event. This large effect indicates workers are likely moving to new locations and not just commuting further.

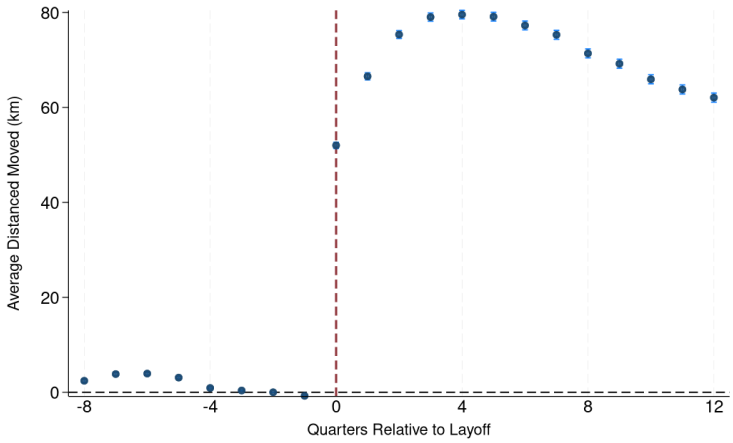


Figure 24: Mass Layoff Impact on Average Migration Distance

B.2 Heterogeneity

While workers who separate from their employer during a mass layoff consistently migrate at higher rates than control workers, there is wide heterogeneity in the level of migration across a range of observable worker, job, establishment, and labor market characteristics. We estimate this by running our analysis interacted with heterogeneous characteristics associated with the worker at the time of separation.

B.2.1 Worker Characteristics

Fig. 25 shows that men on average move 20km further than women. Fig. 26 shows that non-white workers are on average moving 40 km further than white workers. This suggests that non-white workers might be spatially further from areas of opportunity, having to relocate further for their next job.

Fig. 27 shows that while there is far less migration variability among displaced workers by age, young and old workers migrate less far than those in the prime working age between 25-35. Fig. 28 shows us that, college-educated displaced workers migrate further than workers with lower levels of education. Additionally, Fig. 29 shows that white-collar professionals move the furthest, suggesting their labor markets might be less localized. All these findings reaffirm that workers are moving to new labor markets and not commuting further.

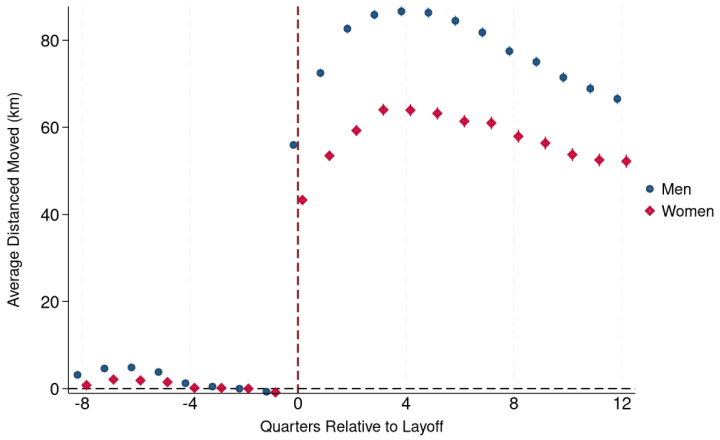


Figure 25: Men migrate further than women

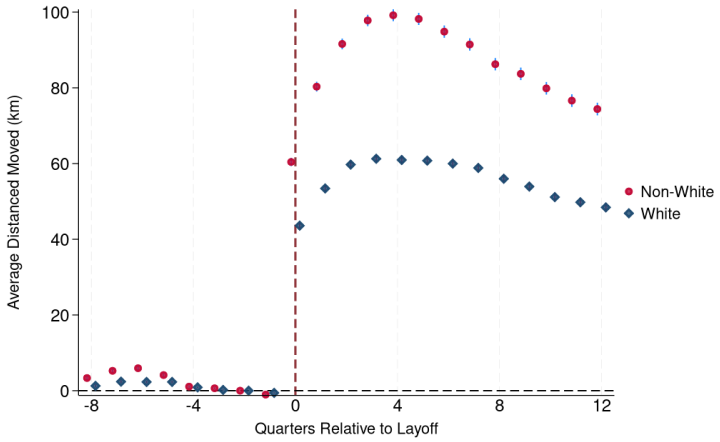


Figure 26: Non-white workers migrate much further than white workers

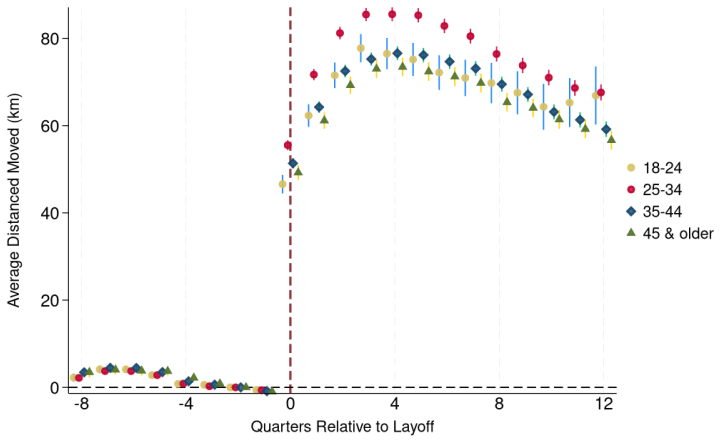


Figure 27: Prime age workers move furthest

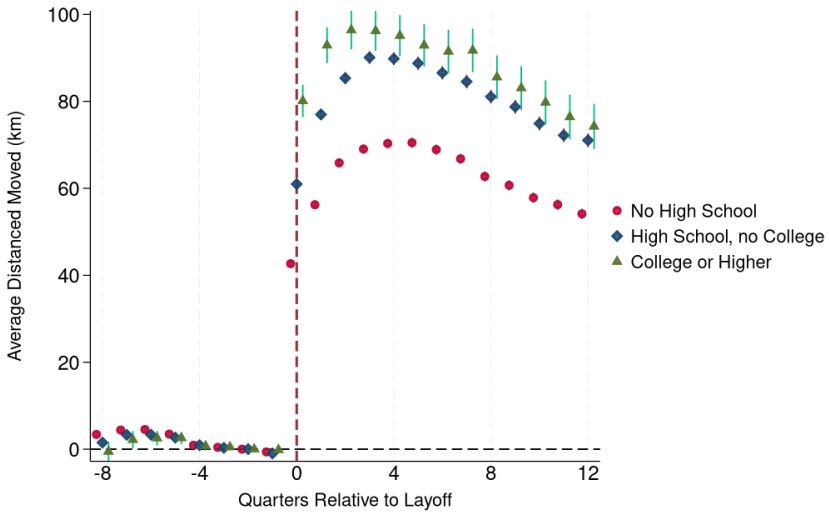


Figure 28: Less educated workers stay closer to their previous job

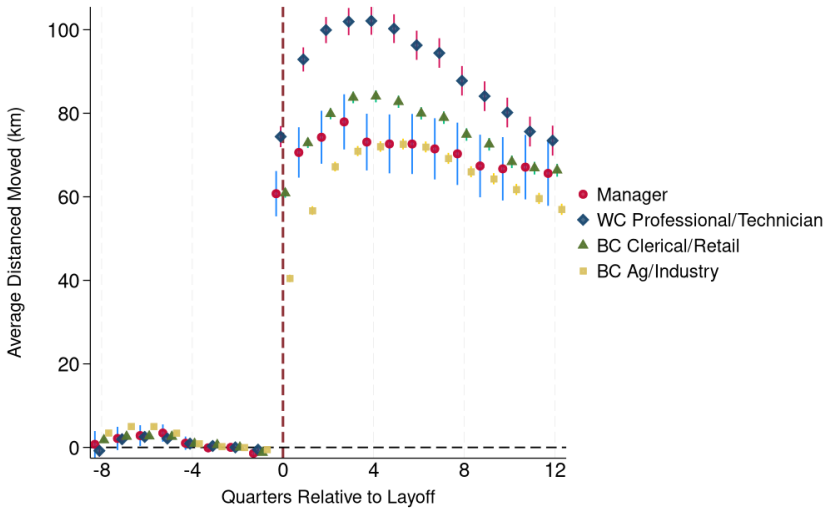


Figure 29: White-collar professionals move furthest

B.2.2 Industry of Establishment

Next, we identify the industry of the establishment from which a displaced worker separates during a mass-layoff and interact it with our event study estimation, comparing treated and control workers of the same industry. We find that workers employed in retail or heavy industry work at the time of separation stay much closer to their previous job when compared to workers in construction, agriculture, or modern services. These findings are displayed in Fig. 30. A summary of average migration distance estimates among displaced workers four quarters after a mass layoff is provided in Table 6

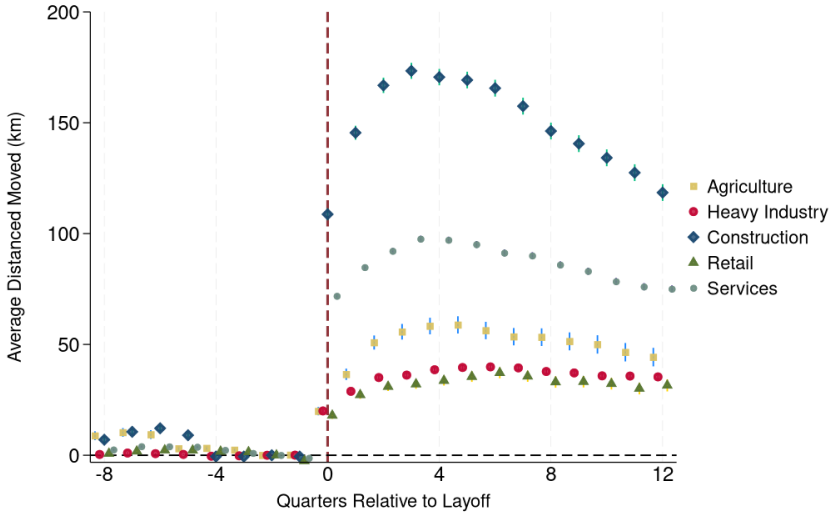


Figure 30: Manufacturing & retail workers migrate far less than workers in other industries

Table 6: Event Study Results - Average Distance Migrated $t + 4$ Quarters after Event

Base, Gender & Race

	(1) All	(2) Men	(3) Women	(4) Non-White	(5) White
Avg. Distance Migrated (km)	79.5681***	86.6351***	63.9378***	99.1706***	60.9458***
	(0.458)	(0.582)	(0.709)	(0.797)	(0.541)
Observations	32,316,102	22,254,204	10,061,898	13,233,507	17,753,022

Education

	(1) No HS	(2) HS, no College	(3) College+
Avg. Distance Migrated (km)	70.3083***	89.8145***	95.1052***
	(0.582)	(0.757)	(2.406)
Observations	17,292,534	13,536,138	1,487,430

Age Group

	(1) 18-24	(2) 25-34	(3) 35-44	(4) 45+
Avg. Distance Migrated (km)	76.4986***	85.5297***	76.5859***	73.4424***
	(1.821)	(0.807)	(0.811)	(1.077)
Observations	2,763,735	12,788,992	11,146,250	5,617,125

Occupation at Treatment

	(1) Manager	(2) WC Prof/Tech	(3) BC Cler/Retail	(4) BC Ag/Ind
Avg. Distance Migrated (km)	73.1067***	102.1237***	84.0453***	72.0369***
	(3.465)	(1.705)	(0.732)	(0.641)
Observations	575,043	3,192,840	12,465,075	15,517,026

Industry at Treatment

	(1) Agriculture	(2) Heavy Ind.	(3) Construction	(4) Retail	(5) Services
Avg. Distance Migrated (km)	58.2914***	38.5809***	170.5859***	33.6674***	97.0747***
	(1.914)	(0.523)	(1.878)	(1.141)	(0.778)
Observations	1,164,198	11,704,518	4,378,626	2,489,130	12,579,630

Notes: Entries report the coefficient on the event dummy at $t + 4$ quarters after mass layoff. Standard errors in parentheses, clustered at the individual level.