BANCO CENTRAL DE COSTA RICA

DOCUMENTOS DE TRABAJO
N.º 04 | 2023

Job Displacement Effects and Labor Market Sorting During COVID-19

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Fotografía de portada: “Presentes”, conjunto escultórico en bronce, año 1983, del artista costarricense Fernando Calvo Sánchez. Colección del Banco Central de Costa Rica.

Efectos del desplazamiento laboral y clasificación del mercado laboral durante el COVID-19

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Las ideas expresadas en este documento son de los autores y no necesariamente representan las del Banco Central de Costa Rica.

Resumen

Este documento estudia los efectos de la pérdida de empleo de los trabajadores. Con datos administrativos detallados de Costa Rica, utilizamos un algoritmo de agrupación para ordenar a los trabajadores en tipos según su estabilidad laboral y eficiencia en la búsqueda de empleo. Nuestros resultados muestran que el desplazamiento laboral conduce a pérdidas de ingresos persistentes para los trabajadores, particularmente durante las recesiones económicas como la pandemia de COVID-19. Los trabajadores desplazados se trasladan a empresas más productivas y con mejor remuneración, especialmente aquellos tipos con un potencial de ingresos inicialmente más alto y con antecedentes de estabilidad laboral. No obstante, los trabajadores también se mueven hacia a ocupaciones con salarios más bajos. Los hallazgos sugieren que se deben considerar los cambios en las características del trabajo en lugar de las características del empleador para explicar las pérdidas de ingresos y la reasignación laboral después de la pandemia.

Palabras clave: Fluctuaciones del ciclo económico, productividad laboral, diferencias salariales, rotación laboral
Clasificación JEL.: E32, J24, J31, J63

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Abstract

This paper examines the effects of job loss on workers. Using detailed administrative data from Costa Rica, we use a clustering algorithm to group workers into types based on their employment stability and job search efficiency. Our results show that job displacement leads to persistent earning losses for workers, particularly during economic downturns such as the COVID-19 pandemic. Displaced workers are moving to more productive and higher-paying firms, especially those types with initially higher earnings potentials and stable employment histories. Nonetheless, these workers are also shifting to lower-paying occupations. The findings suggest that changes in job characteristics rather than employer characteristics should be considered to explain earning losses and labor reallocation in the aftermath of the pandemic.

Key words: Business cycle fluctuations, labor productivity, wage differentials, labor turnover
JEL codes: E32, J24, J31, J63

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May 26, 2023

1. Introduction

The COVID-19 pandemic has led to a significant disruption in the labor market, with many workers facing job loss, reduced working hours, and increased uncertainty. The labor literature has shown that individuals who have been displaced from their jobs experience a permanent loss of earnings, even after they have secured new employment[1]. Furthermore, the dramatic surge in unemployment rates across the globe implies that the economies are facing a process of job reallocation, with workers being forced to shift to new sectors and new types of work in order to secure financial stability.

The vast majority of research on the effects of job displacement has been conducted in developed labor markets such as the United States, Germany, and France. However, the effects of job displacement may vary in developing labor markets, where the social safety net may be weaker and the job search is potentially more frictional. Therefore, it is important to conduct more research on job displacement in developing labor markets

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We thank Laura Juárez, Carlos Urrutia, Benjamín Tello, the Economic Research Department of the Central Bank of Costa Rica and participants of the 2022 Joint Research Program CEMLA Workshop on Labor Markets for helpful comments and suggestions. The views expressed herein are those of the authors and do not necessarily represent the views of the Central Bank of Costa Rica. All results have been reviewed by the Central Bank of Costa Rica to ensure that no confidential information is disclosed.

[1]See Lachowska et al. (2020) for a literature review on the effects of job loss on earnings, household expenditure, children's health, welfare, and criminality.

in order to better understand the specific challenges and effects faced by workers in these regions.

Furthermore, focusing on the consequences of the COVID-19 pandemic on the labor market is critical because the pandemic has resulted in an atypical recession. Unlike previous shocks, the pandemic has caused massive job losses across a wide range of industries, affecting both low- and high-skilled workers. Understanding how the pandemic has influenced the labor market is crucial for policymakers and researchers because it will inform the design of policies and programs to help alleviate the pandemic's negative effects and promote economic recovery.

In this paper, we examine the effects of job displacement on workers' labor outcomes. Job displacement is defined as the permanent loss of a long-term job resulting from mass layoffs[2]. We use detailed administrative microdata from Costa Rica to offer new insights into the labor market adjustment dynamics during the COVID-19 pandemic. Our analysis covers both job losses prior to (including the Great Recession) and during the pandemic, enabling us to compare and contrast the unique impact of the pandemic on the labor market and affected workers. To compute labor dynamics after a displacement, we implement event study methods (as in Davis and Von Wachter (2011), Krolikowski (2017), Lachowska et al. (2020), Schmieder et al. (2022)) to track the labor market effects of displaced workers relative to stayers, both prior to and after the pandemic.

We take a step further by examining *ex-ante* unobservable differences among workers rather than other dimensions of heterogeneity such as differential effects across sectors or industries. For instance, workers differ in human capital, social networks, preferences, and access to information, which determine productivity and search effort differences, ultimately explaining the unequal effect of a recession on workers (Moscarini and Postel-Vinay 2018; Ahn 2022). Specifically, we implement a k-means algorithm to group workers into a small number of types based on individual patterns of job loss and re-employment before the pandemic[3]. Similar to Gregory et al. (2021), we find that demographics and industry do not fully explain the heterogeneity we are

[2]We follow standard definitions of mass layoffs not only to identify a plausibly exogenous separation but also to be able to compare our results with the related literature (e.g., Bertheau et al. (2022)). Research such as Flaaen et al. (2019) and Brandily et al. (2022) have found that using an administrative definition of economic layoffs leads to similar results as relying on mass layoff events.

[3]Recent literature has shown that clustering algorithms are a good alternative to discretize worker and firm types (e.g., Bonhomme et al. (2019, 2022), Gregory et al. (2021)).

capturing.

The algorithm categorizes workers into three types: Type A represents those with higher earning potential and lower chances of job loss. They usually have more education and skills, along with a more secure employment history. They exhibit resilience during economic downturns, bouncing back from earning losses after job displacement much quicker. Type C workers, on the other hand, face longer spells of unemployment, have lower education, and have a less secure employment history. Lastly, worker type B refers to those with moderate characteristics, lying between the other two worker types.

Our results indicate that displaced workers suffer persistent earning losses, particularly during economic recessions, including the COVID-19 pandemic. For Costa Rica, the extensive margin is central to understanding the job loss costs, i.e., struggling to find a job is a major determinant in job earnings recovery after a displacement. Regarding the pandemic recession, we do not find significant differences in earning losses across worker types, even for those individuals that were previously characterized by standing employment relationships and faster job finding, consistent with the disruptive nature of the COVID-19 shock and the extensive health and mobility restrictions implemented during 2020. The lack of heterogeneity could potentially be attributed to the fact that we are studying an early period during which the labor market is still experiencing the adverse effects of the pandemic[4].

In terms of worker reallocation, our findings demonstrate that during the pandemic, displaced workers moved to establishments that were more productive and offered higher pay than their previous employers. Hence, employer characteristics are not a significant factor in explaining earnings losses. We examine changes in job characteristics, showing that displaced workers are moving to lower-paying occupations. The reallocation dynamics are more pronounced for workers of types A and B, although differences are still narrow by the third quarter of 2022. These results give us a new understanding of the economic impact of job displacement on both workers and firms. Further research should explore the "productivity-enhancing" nature of labor realloca-

[4]As of the third quarter of 2022 (the last period of available data used in this paper), the unemployment rate in Costa Rica was 12.0 percent, which is 2 p.p. higher than the average from 2015–2019 and still above its natural rate of unemployment. This implies that the reallocation process after the pandemic has not been completed, as a large number of unemployed workers remain searching for a job.

tion during downsizing events and the role of occupational dynamics.

The empirical evidence we collect suggests that the labor market is still adjusting to the new economic conditions and that the reallocation process is still ongoing during our period of analysis. By the time we write this paper, unemployment rates are much higher than the average 2015–2019 levels (see Figure A4 in the Appendix), indicating that a significant number of workers are still transitioning back to employment. Nonetheless, the paper provides fertile ground for a follow-up on this topic for a developing country like Costa Rica, as we provide sorting dynamics during the first phase of the pandemic. With a more mature recovery process, we will be able to evaluate the empirical findings—especially the reallocating patterns and assortative sorting—under the lens of a model that sheds more light on mechanisms and economic intuition. More research is needed to understand the sorting dynamics between workers and firms after a major recession in developing labor markets.

The paper is organized as follows: Section 2 summarizes the administrative data and presents some descriptive statistics. In section 3, we detail our empirical strategy to discretize the unobserved worker heterogeneity, and then we characterize the defined worker types. Section 4 explains the empirical definition of job displacement and our event study framework to track worker dynamics after being displaced. And finally, Section 5 presents the main results, and Section 6 discusses policy implications and avenues for future work.

Related literature and contribution

This paper offers new insight into the costs of job loss during a recession by focusing on the labor-adjusting dynamics of a developing labor market. Prior studies have primarily examined developed markets such as the U.S. (e.g., Krolikowski (2017), Flaaen et al. (2019)) and Europe (e.g., Bertheau et al. (2022), Brandily et al. (2022), Schmieder et al. (2022)). Our research sheds light on the challenges and outcomes faced by workers in a more frictional labor market. This expanded understanding of labor market dynamics can inform policymakers and employers on how to better support workers during economic downturns, as well as provide empirical evidence to discipline job ladder (Moscarini and Postel-Vinay (2018)) and occupational mobility models (Guvenen et al. (2020)).

This article also makes a significant contribution to the literature on labor market reallocation dynamics following a recession. The literature focuses primarily on the 2008-2009 Great Recession's displacements (e.g., Lachowska et al. (2020) and Schmieder et al. (2022)), and little is still known about the COVID-19 recession's adjustment dynamics. We show enduring earnings losses for displaced individuals, and we contribute by assessing the role of reallocation in explaining such job loss costs. As Schmieder et al. (2022), we document that job displacement is a particularly costly phenomenon during recessions.

Our findings contrast with recent literature attributing changes in employer characteristics to the estimated earning losses. Brandily et al. (2022), Bertheau et al. (2022), Schmieder et al. (2022) find that workers reassign to more productive but worse-paying firms. Our early findings emphasize the role of occupational switching and changes in the new job characteristics, which connect to dynamics related to the job ladder (Burdett et al. (2020), Jarosch (2021), and Audoly et al. (2022)).

We further provide a novel perspective on how the pandemic impacted workers and how they responded to labor market disruptions. By examining unobserved worker heterogeneity, our study indicates that the pandemic had a significant and widespread effect on workers, which is consistent with the massive disruptions caused by the pandemic. Hence, this paper builds a bridge with the existing literature that has shown that certain groups of workers, such as those in low-paying occupations, those with lower levels of education, women, young workers, and minority groups, were disproportionately affected by the pandemic (Cortés and Forsythe 2023). Additionally, our paper also connects with the literature on the compositional changes in the pool of unemployed over the business cycle (e.g., Mueller (2017)), as we show that the pandemic significantly impacted workers who, in normal times, experience longer employment relationships and shorter unemployment spells.

Finally, our work can be linked to the literature showing that the composition and labor market dynamics during the recession can have sizeable implications for monetary policy (Ravenna and Walsh 2022), as well as related public policy analysis on employment safety nets, inequality, and strategies to mitigate the negative effects of recessions.

2. Data

We use rich administrative information to construct a comprehensive linked employer-employee dataset. The panel tracks the firms' productivity and profitability as well as high-frequency (monthly) employment-match characteristics such as monthly wages, occupations, job-to-job transitions, and firm dynamics. The data covers the period from January 2006 to October 2022.

Specifically, the panel is built on social security data. For each worker, this data records, on a monthly basis, information on demographic characteristics (e.g., date of birth, nationality, sex), labor earnings, and occupation at each job. We track employers by their unique corporate tax ID. Monthly labor earnings are not censored, and we use the universe of workers and firms in the formal sector. The occupation is recorded as a standardized four-digit ISCO-08 code. Like most matched employer-employee datasets, the information does not contain the number of hours worked and does not track informal employment[5].

We add to the linked dataset firm-level balance sheet variables from the universe of corporate tax returns from 2005 to 2021 to define the industry, estimate labor productivity, and corroborate firm dynamics, job transitions, hirings, and separations.

We follow standard data cleaning techniques (See Sorkin (2018), Gregory et al. (2021), Crane et al. (2022) and references within) oriented to precisely estimate the occurrence and timing of job transitions, construct monthly wages in the absence of hours worked, and rank workers, occupations, and firms.

2.1. Sample selection

Sample selection follows Krolikowski (2017), Flaaen et al. (2019), and Bertheau et al. (2022)[6]. We impose standard tenure restrictions that the worker must have had at least two consecutive quarters with an employer, and we omit all earnings histories with

[5]Informality rates for employed individuals aged 15 to 64 are 30 %-, smaller than in other Latin American countries (e.g., Mexico 55%, or Argentina 47 %) but higher than the OECD average (17%) (OECD, 2017). Nonetheless, during the pandemic, Costa Rica's informal sector shrank and recovered much slower than the informal sector, consistent with Leyva and Urrutia (2023).

[6]We put special emphasis on the recommendations on how to select the control group (Krolikowski 2017) and construct a harmonized dataset to identify job loss costs (Bertheau et al. 2022)

a calendar year of zeros in the four years following any separation. We want to avoid individuals that are marginally attached to the labor force to improve the precision of the estimated dynamics.

3. Classification of workers

We follow Gregory et al. (2021) and Bonhomme et al. (2019, 2022) to discretize worker heterogeneity based on *ex-ante* patterns of employment transitions between 2009 and 2019. First, we compute the monthly frequency history of employment transitions for the universe of workers in Costa Rica's labor market. For each individual, we estimate their complete distribution of duration of different non-employment spells[7]. Then, we use a k-means algorithm to form clusters of workers based on common factors that define their employment history. Since the chosen method is an unsupervised algorithm, as we do not observe the types, we follow Wang (2010) to define the optimal number of types[8].

More precisely, for each individual worker i, we compute their:

- Distribution of employment spells: $e^i_{1,6}$ (1 to 6 months), $e^i_{6,12}$ (6 to 12 months), $e^i_{12,+}$ (more than 12 months), with $\sum_t e^i_t = 1$ for each individual worker i.
- Distribution of nonemployment spells: $u^i_{1,3}$ (1 to 63 months), $u^i_{3,6}$ (3 to 6 months), $u^i_{6,12}$ (6 to 12 months), $u^i_{12,+}$ (more than 12 months), with $\sum_t u^i_t = 1$ for each individual worker i.
- Proportion of time in non-employment, ud^i.
- Worker fixed-effect a_i from an AKM model (Abowd et al. (1999)), interpreted as a combination of skills and other factors that are rewarded equally across employers. The worker fixed-effect captures unobserved differences that explain wage dispersion across workers.[9]

[7]We do not observe if the worker enters unemployment or moves out of the labor force, which posits an important limitation. Nonetheless, we focus on displaced workers during a mass layoff, which likely suggests a worker's transition to unemployment.

[8]It is possible to define a more refined partition of the data, as desired. Our algorithm indicates that the appropriate number of clusters is $k = 3$, based on standard elbow and silhouette methods.

[9]For worker i in year t while employed at a firm $j = J(i, t)$, we estimate the model $y_{ijt} = \alpha_i + \psi_{jt} + X_{it}\beta + \varepsilon_{ijt}$ as in Card et al. (2013) and Engbom et al. (2022) where y_{ijt} is log earnings, α_i is the worker fixed-effect, ψ_{jt} is a firm-year fixed-effect, X_{it} is a vector of time-varying worker controls with coefficient vector β

We feed into the clustering algorithm the employment history described above to perform the identification of worker types. We consider standard techniques to deal with the curse of dimensionality and avoid model overfitting.

3.1. Workers types

Our unsupervised method coincides with Gregory et al. (2021) in identifying three well-defined groups of workers, which we label as types A, B, and C. Table 1 provides further information on the main characteristics of each worker type. Type A workers are characterized by their long-lasting employment relationships and brief spells of unemployment. These individuals typically hold stable jobs, remain in the same position for extended periods, and rarely experience joblessness. Additionally, they earn relatively higher wages and possess higher abilities compared to other worker types. On the other hand, Type C workers face difficulty securing employment and tend to suffer long periods of unemployment. They struggle to establish employment relationships and may experience job insecurity. These workers earn lower wages and have lower ability levels compared to others. Type B workers, meanwhile, fall in between the other two types in terms of maintaining employment matches or finding new ones. Although they are neither as stable as Type A workers nor as unstable as Type C workers, they may experience unemployment, but to a lesser extent than Type C workers. In terms of gender composition, all types exhibit a larger share of male workers[10], but female participation is higher in the group C.

(a restricted set of age dummies for each gender-education group), and ε_{ijt} is an error term. The study addresses the limited mobility bias problem in the AKM model by using a large panel and introducing time-varying fixed effects.

[10] In 2021 Costa Rica had one of the lowest female participation rates (75.6%) among the OECD members (average of 78.0%) . Source: OECD.

TABLE 1. Descriptive Statistics for Each Worker Type

	Type A	Type B	Type C	All
Group share (%)	42.8	41.2	16.0	100.0
	Job duration (%)			
<6 months	9.5	42.0	27.8	25.8
6-12 months	6.5	19.5	20.1	14.0
12 months or more	84.0	38.5	52.2	60.2
	Non employment duration (%)			
<3 months	95.8	27.4	10.9	54.0
3-6 months	1.6	31.0	3.6	14.0
6-12 months	1.2	28.4	5.3	13.1
12 months or more	1.4	13.1	80.2	18.9
Fraction of time non-employed (%)	1.7	23.8	46.7	18.0
Worker AKM FE	13.38	13.08	13.09	13.21
Annual earnings US$	13,398	8,040	8,118	10,344
Age	34.88	30.95	31.41	32.71
Proportion males	60.6	68.1	55.3	62.8

Notes: Descriptive statistics for the 2015-2019 period. For job duration and nonemployment duration, this table shows the percentage of individual spells within each specified time interval, adding up to 100% for each worker type. Annual earnings expressed in December 2020 USD. The sample size for the number of workers is 1,562,902.

Intuitively, we are using each worker's employment history to categorize them based on their ability to keep a job or find a new one after being nonemployed. Based on frictional models featuring a job ladder (e.g., Mortensen (2005), Moscarini and Postel-Vinay (2018), Krolikowski (2017)) and occupational dynamics (e.g., Guvenen et al. (2020), Baley et al. (2022)), employment histories are strongly correlated with heterogeneity in the search effort, worker preferences, social networks, worker productivity, and other relevant unobserved worker characteristics that govern labor market transitions and compositional changes in unemployment during recessions[11]. Moreover, in frictional labor markets, some individuals will end up in poor-quality matches after non-employment, so they will need to transition from job to job until finding a suited position. Although observable characteristics such as sex, race, and education can explain the potential heterogeneity in the displacement effects across workers, the empirical evidence suggests that unobservable characteristics governing individual employment dynamics explain

[11]As explained by Mueller (2017), these unobserved factors play a key role in explaining shifts toward high-ability or high-wage workers during recessions.

much more of workers' behavior after a job separation (Ahn 2022; Ravenna and Walsh 2022)[12]. Our clustering algorithm precisely discretizes such unobserved heterogeneity.

To assess if the defined worker clusters are consistent with the economic intuition that we have discussed throughout the paper, we conduct an event study framework to compare labor market outcomes across the different worker types. In particular, we track earnings and probabilities of being employed after a plausibly exogenous job displacement prior to 2020. We will define more explicitly how we identify job separation in the next section. More precisely, we run the following regression:

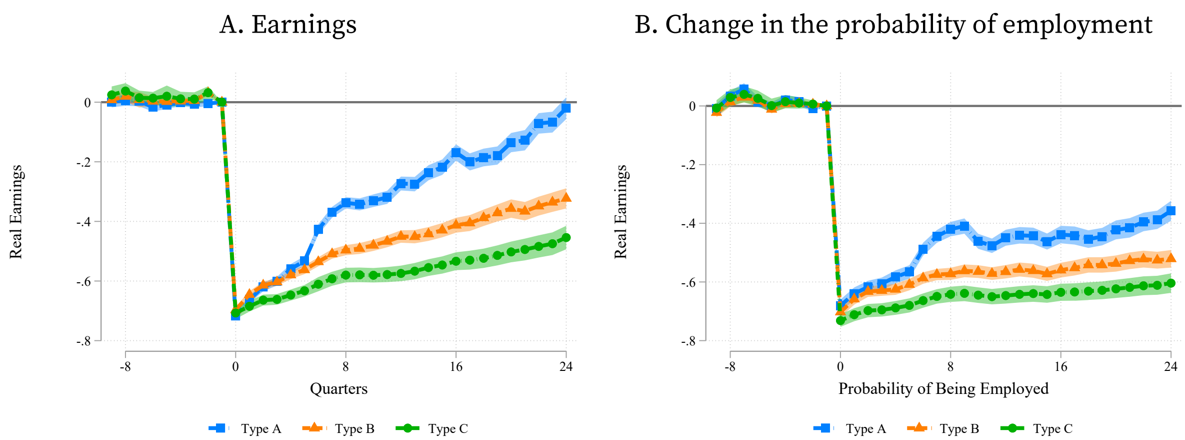
$$e^{q}_{it} = \alpha^{q}_{i} + \gamma^{q}_{t} + \vec{X}_{it}\beta^{q} + C^{c}_{i} \times \sum_{k=-10}^{24} \delta^{q}_{c,k} D^{k}_{it} + u^{y}_{it}, \quad t = k + q, \tag{1}$$

With e^{q}_{it} is the individual i's labor outcome in quarter t, a^{q}_{i} a worker fixed-effects, γ^{q}_{t} are time fixed-effects, $\vec{X}_{it}$ is a quartic polynomial in the age of worker i in quarter t, the D^{k}_{it} are dummy variables equal to 1 in the k-th quarter relative to the displacement happened at quarter q, with $k = 0$ denoting the quarter when the displacement occurs. u^{q}_{it} the error term. The model (1) features a dummy variable C_i interacting with the recovery path coefficients δ^{q}_{k} to capture differences across worker types, indexed by $c \in \{A, B, C\}$. The coefficients $\delta^{y}_{c,k}$ measure the earnings path of the time q displaced worker relative to the stayers. We normalize $\delta^{q}_{c,-1} = 0$, and standard errors are clustered at the individual level. Given the inclusion of time fixed-effects, the $\delta^{y}_{c,k}$ captures the earnings effect dynamics for displaced workers relative to employed workers. We emphasize that the classification algorithm to define worker types is conducted simultaneously with this event study (2008–2019), so there is a potential endogeneity issue that may bias the differences across groups. Hence, the analysis by worker types serves only an illustrative purpose: to shed light on the worker types identified by our unsupervised algorithm. Such a concern is alleviated for the pandemic analysis, as we consider *ex-ante* heterogeneity.

[12]For instance, some workers may experience a decline in their human capital, as their skills become less relevant or out of date. Additionally, displaced workers may have to accept lower-paying jobs, either because they have fewer skills or because they are in less demand. Furthermore, displaced workers may experience a reduction in their social networks and a decline in their reputation, which can make it harder for them to find new job opportunities that are in line with their skills and experience.

Figure 1 summarizes the main results for earnings and employment probabilities[13]. Figure 1A suggests large and persistent earnings losses for all worker types, with Type *A* returning to their pre-layoff earnings six years after the separation. Figure 1B displays the change in the worker's probability of being employed, indicating that worker type *A* is characterized by faster job-finding rates than type *B* and type *C*, in line with the descriptive statistics summarized in Table 1 and analyzed previously.

FIGURE 1. Labor Dynamics by Worker Types (Prior to 2020)



Notes: The panel displays the earnings effects and the change in the probability of being employed dynamics for workers who suffered a job displacement between 2009 and 2019 at quarter $q = 0$, relative to stayers. The figures are jointly estimated with a 95% confidence interval, calculated using clustered standard errors at the individual worker level.

As in Gregory et al. (2021), we show that the worker types derived from the clustering algorithm cannot be fully explained by observable factors such as gender, birth year, skill level, or industry. Table 2 presents the results of a multinomial logit regression on the probability of being a specific worker type based on observable characteristics and industry-specific fixed effects. Although the coefficients are consistent with the descriptive statistics in Table 1, the low pseudo R-squared of the regression (7.2%) compared to the high pseudo R-squared (82.3%) from a regression that includes employment histories used in the k-means algorithm suggests that worker types are better explained by unobserved factors rather than demographics and industry. This aligns with recent research indicating that unobserved worker heterogeneity plays a key role in explaining unemployment and reallocation patterns (e.g., Bonhomme et al. (2019, 2022), Ahn (2022)).

[13]A worker is employed if she has any positive labor earnings during at least one quarter.

Table 2. Multinomial logit coefficients for demographics on worker types

	Observales only		**Observables and employment history**	
	Group 2	**Group 3**	**Group 2**	**Group 3**
Male	0.045***	-0.466***	0.032	-0.086***
	(0.004)	(0.005)	(0.020)	(0.022)
Birth year	0.027***	0.018***	0.004***	0.006***
	(0.000)	(0.000)	(0.001)	(0.001)
Skill group (Based on occupation)				
Medium	-0.270***	-0.299***	-0.090***	-0.087***
	(0.005)	(0.007)	(0.023)	(0.025)
Medium-High	-0.800***	-0.762***	-0.182***	-0.171***
	(0.007)	(0.009)	(0.033)	(0.035)
High	-1.316***	-1.036***	0.000	0.014
	(0.007)	(0.009)	(0.037)	(0.040)
Constant	-51.871***	-35.713***	86.620***	75.973***
	(0.363)	(0.466)	(1.828)	(1.987)
Number of workers	1,562,902		1,562,902	
Industry-FE	Yes		Yes	
Pseudo R2	0.072		0.823	

Notes: Standard errors in parenthesis. * $p < 0.05$,** $p < 0.011$,*** $p < 0.001$. The table shows the coefficients for a multinomial logit on demographics by worker types. The first two columns include worker characteristics only, while the last two columns include the worker's employment transition history used for the clustering algorithm. Industry fixed-effects are included in all regressions.

4. Identification of job displacement effects

Our main goal is to estimate the treatment effect of job displacement on workers under an event study framework to (i) evaluate its impact in terms of earnings inequality, (ii) assess its persistence, and (iii) identify heterogeneous effects across worker types. Consequently, we need to clearly define the *treatment*, i.e., a job displacement, and both the *treatment* and *control* groups.

Job displacement. We focus on mass layoffs to estimate the effects of job displacement, both prior to and due to COVID-19. Since we do not observe the reason for the employment separation, we must identify those events that are likely to be involuntary in order to avoid endogenous separations[14]. As shown by Flaaen et al. (2019), the best alternative is to rely on administrative data to identify establishments that suffered an episode of large employment contraction. Concretely, a firm with at least 50 employees whose monthly employment (i) decreased by at least 30%[15] and (ii) does not return to its initial size (or above) within the subsequent 12 months. Intuitively, this empirical strategy assumes that these are involuntary separations owing to economic distress. Table 3 shows some descriptive statistics of the establishments identified as suffering a mass layoff.

TABLE 3. Descriptive Statistics for Mass Layoffs

	Great Recession	**2010-2019**	**COVID-19**
Number of firms	123	408	110
Average firm size (employment)	138	116	112
Median monthly wage pre-layoff, laid-off workers	553.6	590.9	566.4
Median monthly wage pre-layoff, all workers	627.4	679.6	709.5

Notes: A mass layoff is defined as a cut of 30% or more in employment for firms with at least 50 workers. Monthly wages are expressed in 2020 USD (584.9 colones per USD). We include mass layoffs that occurred between January 2015 and December 2021. The last row includes the average monthly wage for all workers who were employed at those firms at the time of the mass layoff.

To gain a more comprehensive understanding of the cyclical differences in earnings losses resulting from job displacement, we have analyzed three distinct periods. The first period covers job displacements that occurred during the Great Recession, from 2008 Q2 to 2009 Q1. During this period, Costa Rica experienced negative GDP growth rates (see Figure A5 in the Appendix). The second period encompasses "normal times", or a period of relative macroeconomic stability, from 2010–2019. The third period focuses specifically on job losses due to the COVID-19 pandemic, with worker displacements taking place from February 2020 to December 2020[16].

[14]For instance, workers who voluntarily quit to get a better job.

[15]This threshold is standard in the literature. See Davis, Flaaen et al. (2019), Bertheau et al. (2022).

[16]As shown in Barquero-Romero et al. (2022), production and electricity consumption declined between March and November 2020 (see Figure A1). Labor market data indicates that Costa Rica's unemployment rates and transitions from employment to unemployment started to peak in February 2020.

Treated group. Our *treated* group consists of all individuals who lost their job when their employer firm was suffering a mass layoff episode. The monthly frequency of our data allows us to precisely pin down the timing (either month or quarter) when the separation occurs.

Control group. Similar to Krolikowski (2017) and Flaaen et al. (2019), our control group is composed of individuals who do not lose their job in a particular period of time and were employed by a relatively stable firm, which we define as firm growth in the growth interval (a firm with employment and wage bill growth within [-5 percent, +5 percent])[17].

Event study. We estimate the effects of job displacement on labor market outcomes over various time horizons, as in Davis and Von Wachter (2011), Krolikowski (2017), and Flaaen et al. (2019). In this case, we construct a monthly event study that basically compares the treatment (displaced workers) and control groups (non-displaced workers) to point out earnings differences that would have happened in the absence of the separation. Specifically, we consider the following models:

$$y_{it}^{m} = \alpha_i^{m} + \gamma_t^{m} + \vec{X}_{it}\beta^{m} + \sum_{k=-10}^{24} \delta_k^{m} D_{it}^{k} + u_{it}^{m}, \quad t = k + m, \tag{2}$$

$$y_{it}^{m} = \alpha_i^{m} + \gamma_t^{m} + \vec{X}_{it}\beta^{m} + C_i^{c} \times \sum_{k=-10}^{24} \delta_{c,k}^{m} D_{it}^{k} + u_{it}^{y}, \quad t = k + m, \tag{3}$$

The dependent variable y_{it}^{m} is the individual's i labor market outcome (e.g., real earnings), a_i^{m} an individual fixed-effects, γ_t^{m} are time fixed-effects, $\vec{X}_{it}$ is a quartic polynomial in the age of worker i in month t, the D_{it}^{k} are dummy variables equal to 1 in the k-th month relative to the displacement happened at quarter q, and u_{it}^{m} the error term. The model (1) adds a dummy variable C_i interacting with the recovery path coefficients δ_k^{m} to capture differences across worker types $c \in \{A, B, C\}$. The coefficient δ_k^{y} and $\delta_{c,k}^{y}$ measure, respectively, the earnings path of the time m displaced worker

[17] As explained by Flaaen et al. (2019), this sample selection is to have a control group or counterfactual not experiencing either a positive or negative shock.

relative to non-displaced peers, and we normalize $\delta^m_{-1} = 0$ and $\delta^m_{c,-1} = 0$. We estimate standard errors clustered by individual workers.

Selection into treatment. One important concern is whether the selection into treatment is asymmetric across the identified worker types. If a particular type is significantly more likely to experience job loss during COVID-19, then it may reflect that our treatment definition and the identification of worker types are not plausibly exogenous, biasing the magnitude and interpretation of our coefficients of interest. Table 4 shows the results of a linear probability model on the probability of being displaced after January 2020, the pandemic period. We find that there is no statistically significant difference between the three worker types, suggesting that selection into treatment is not asymmetric[18]. All coefficients associated with the worker type are statistically non-significant and pretty close to zero.

TABLE 4. Probability of Job Displacement by Worker Types

	1-month (1)	**3-months (2)**	**6-months (3)**
Type B	-0.000209	0.0000693	0.000265
	(0.000516)	(0.000465)	(0.000242)
Type C	0.000865	0.000843	0.000387
	(0.000753)	(0.000681)	(0.000354)
Obs.	14,904	14,904	14,904

Notes: Standard errors in parenthesis. * $p < 0.05$,** $p < 0.011$,*** $p < 0.001$. The table shows the results of a linear probability model in which the dependent variable is a dummy for suffering a job displacement after January 2020 (the pandemic period), with Type A as the baseline category. Columns (1), (2), and (3) restrict to suffering the job displacement one month, three months, and six months ahead. The regression controls for age, gender, occupation, industry, and quarter fixed-effects. The model shows that there are no differences in the probability of suffering a job displacement across worker types.

Firm and occupation-level characteristics. We estimate *ex-ante* firm and occupation-level characteristics relative to the pandemic period (2020–2021) as we seek to identify reallocation or sorting patterns, i.e., if displaced workers move to more productive and higher-paying establishments and jobs. To alleviate identification concerns that job losses and worker allocation contribute directly to firm performance and within-occupation wages, we restrict information to 2010 and 2019, as available[19]. Therefore,

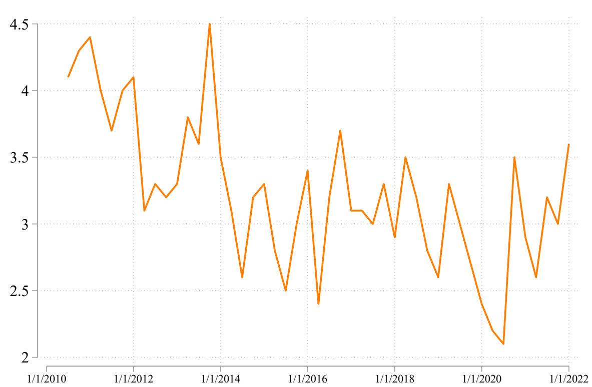
[18] Furthermore, Figure 4 shows no statistically significant pre-trends between worker types more than two years before the displacement event. We expand the discussion on this result in Section 5.1.

[19] Early empirical evidence suggests that the pandemic and recovery have induced restructuring of firms, occupations, and industries (e.g., Haltiwanger (2022)). We want to avoid firm dynamics after the

we do not speak about productivity and wage dynamics after COVID-19. Similar to the tenure restriction imposed on workers, we consider firms operating in January 2020 with at least three years of prior information[20]. To rank firms and occupations, we compute the *ex-ante* average of the specific firm and occupation-level characteristics using our administrative microdata covering the universe of workers and firms in the labor market.

Limitations coming from lack of informal sector information. One of the primary limitations of this study is the lack of information on the informal sector, as our analysis relies on administrative social security data. This omission introduces a potential measurement error, as some workers may transition to the informal sector instead of becoming unemployed. Consequently, there is a risk of overestimating the earning losses if this transition is a significant determinant of movements from formal employment to nonemployment. However, the empirical evidence presented in Figure 2 suggests that flows from formal employment to informal employment are relatively small and exhibit no discernible trend over the past decade. Approximately 2.5% to 4.5% of formally occupied workers make this transition, and the magnitude of such transitions has been declining over time. These findings imply that persistence in informal employment is substantial, and most of the inflows into the informal sector come from new workers entering the labor market through informal channels.

FIGURE 2. Transition Rate: Formal Employment to Informal Employment



Source: National Institute of Statistics and Census (INEC).

pandemic as it would bias the estimated reallocation effects.

[20]We seek to avoid firms already closing their operations or already experiencing idiosyncratic shocks.

5. Results

This section presents the results on the effects of job displacement on workers. We begin by analyzing the earning losses experienced by displaced workers and then move on to examine the reallocation dynamics in the labor market. Specifically, we look at how displaced workers move to new firms and jobs and how these new jobs compare in terms of productivity and pay. We also investigate whether there are any differences in the reallocation patterns between different groups of workers.

Throughout our analysis, we consistently document that the individual workers who have been displaced do not have systematically different characteristics or labor market outcomes prior to the displacement compared to those who have not been displaced. In other words, there are no pre-trends between the treated and control groups, which eventually would allow us to draw causal inferences about the effects of job displacement on workers.

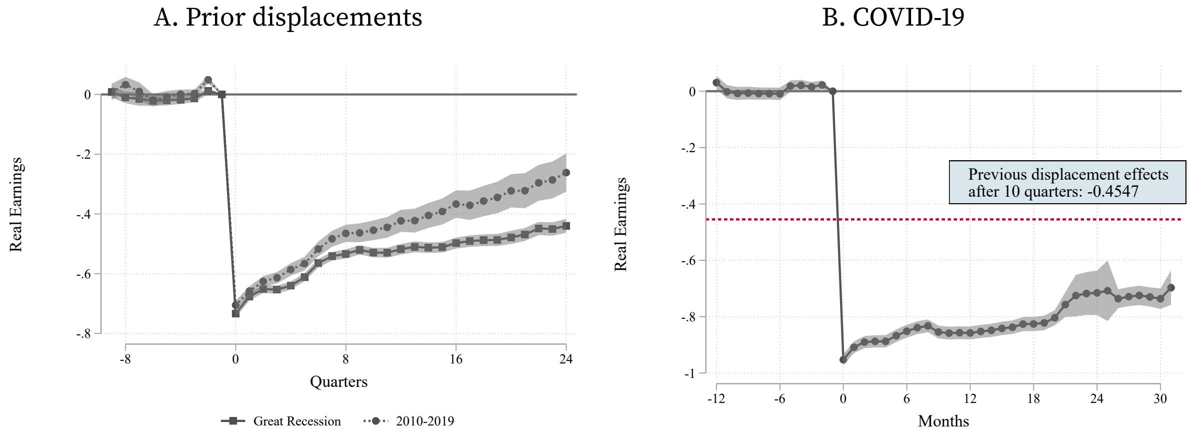
5.1. Earning Effects of Job Loss

Figure 3 presents the results of our analysis on the impact of job displacement on labor earnings for all workers in our sample. Figure 3A focuses on displacements that occurred prior to 2020, differentiating between those layoffs during the Great Recession (GR) and during the 2010–2019 period. Job loss leads to significant and long-lasting earnings losses for affected workers, and the impact is deeper during recessions. Our estimates show that in the year following a displacement, earnings decline by 58.6 percent (63.98 during the GR) and by 26.2 percent (43.97 for the GR) six years after the job separation when compared to workers who were able to maintain their employment[21]. It is important to note that this inference encompasses both the intensive and extensive margin of displacement, i.e., includes non-employed workers who have zero earnings[22]. The much deeper effect during the COVID-19 pandemic aligns with Schmieder et al. (2022), who find that earnings losses after displacement are highly cyclical, nearly doubling in size during downturns.

[21]Schmieder et al. (2022) document a reduction in annual earnings of about 15% lasting at least 15 years for Germany

[22]These results are further reinforced by Figure A2 showing that even when excluding zero observations, displaced workers still experience a slower earnings recovery and lingering negative effects, with earnings remaining around 10 percent lower six years after the separation.

Figure 3. Earnings Effects for Displaced Workers

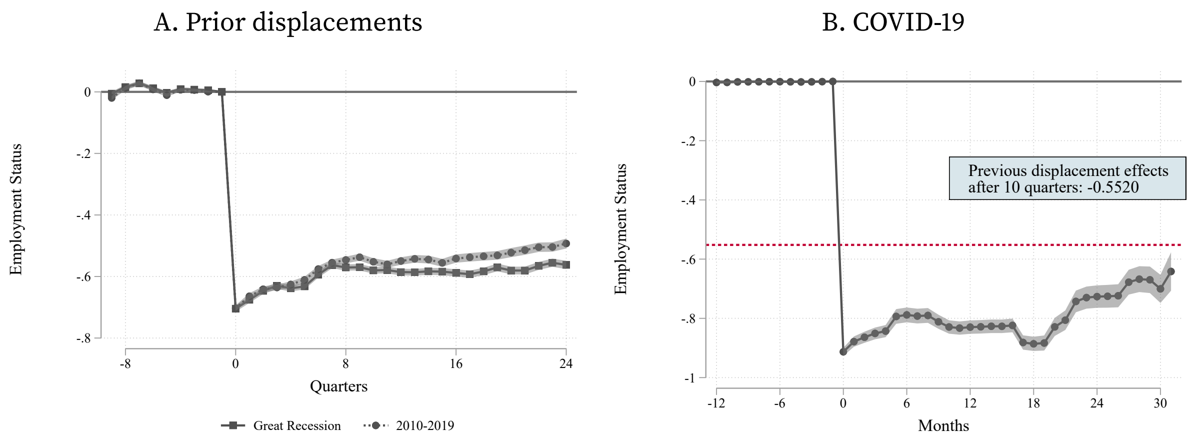


Notes: The panel shows the earnings effects for workers who suffered a job displacement at quarter $q = 0$ (2009-2019) and month $m = 0$ (pandemic period), relative to stayers, jointly with a 95% confidence interval estimated with clustered standard errors at the individual worker level. The red line in the right plot denotes the earnings effect 30 months after a displacement for layoffs before the pandemic.

Figure 3B focuses on the COVID-19 pandemic and reinforces the cyclicality of earning losses. Despite the short time frame of only 30 months (10 quarters) since the onset of the crisis, it is clear that the impact on earnings has been more severe than the average effect observed in previous displacements, including the Great Recession. Specifically, by the first year after a displacement, workers' earnings had declined by 89 percent compared to those who were able to maintain their employment. Furthermore, the recovery path for these workers has been slower than what has been observed in prior displacements. Even two and a half years after the layoff, earnings for these workers remained 69.8 percent lower than for the control group. In contrast, for prior displacements, the estimated effect for the same time window was around 45.5 percent for events between 2010 and 2019 and 51.5 percent for layoffs during the Great Recession.

The more pronounced effect of job displacement during the COVID-19 pandemic can be mainly attributed to the greater challenge that workers face in finding new employment, as evidenced in Figure 4. The negative impact on the likelihood of being employed among those who lost their jobs during the pandemic is considerably greater than before, and this trend persists over time. This finding is in line with the high unemployment rates in Costa Rica, emphasizing the additional hurdle of finding a job during the pandemic. Consequently, the more severe earnings impact observed for the COVID-19 shock is strongly linked to the difficulties that workers encounter in re-entering the labor market.

FIGURE 4. Job-Finding Dynamics for Displaced Workers



Notes: The panel shows the change in the probability of being employed (and therefore, job-finding dynamics) for workers who suffered a job displacement at quarter $q = 0$ (2009-2019) and month $m = 0$ (pandemic period), relative to stayers, jointly with a 95% confidence interval estimated with clustered standard errors at the individual worker level. The red line in the right plot denotes the earnings effect 30 months after a displacement for layoffs before the pandemic.

Our findings on earnings and job-finding dynamics align with the trends seen in Costa Rica's overall unemployment rate. The unemployment rate saw a permanent rise after the Great Recession, which is in line with an increase in the natural rate of unemployment (Garita and Sandoval-Alvarado 2022). Unlike the U.S., the unemployment rate in Costa Rica did not recover post-2008. Regarding the pandemic period, as of the third quarter of 2022, the unemployment rate in Costa Rica was 12.0 percent, which is 2 p.p. higher than the average from 2015–2019 and still above its natural rate of unemployment. This implies that the reallocation process after the pandemic has not been completed, as a large number of unemployed workers remain without employment.

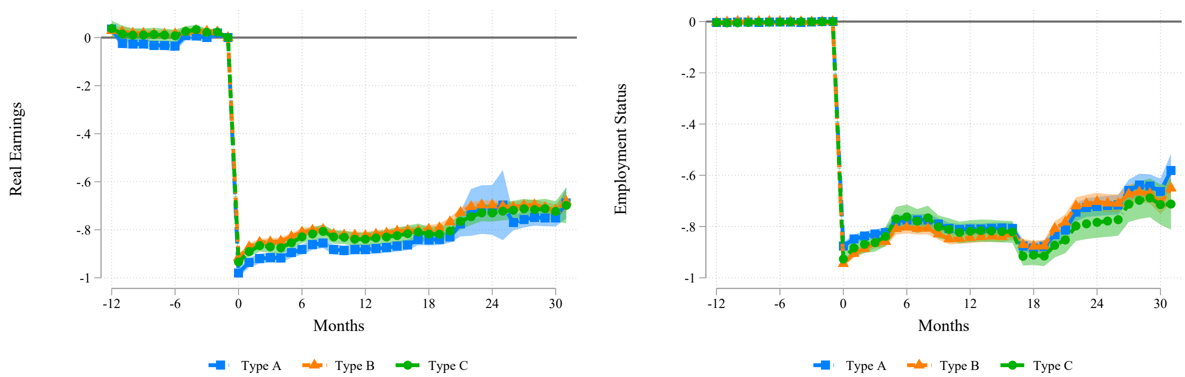
Compared with other studies, the magnitude and persistence of the earning losses that we infer for Costa Rica are similar to those documented by Bertheau et al. (2022) for southern European countries (Italy, Spain, and Portugal). Using harmonized data and a comparable research framework, Bertheau et al. (2022) compute earning losses 10 years after displacement at approximately 30% for southern European countries (Italy, Spain, Portugal) and 10% for Scandinavian countries. For Costa Rica, our calculations reveal earning losses of 26.2% six years after displacement for job losses occurring between 2010 and 2019, in contrast to 46.9% observed during the Great Recession.

Initially, the pandemic affected worker types similarly.. Our analysis indicates that the three worker types, grouped by unobserved heterogeneity, were affected similarly by the pandemic in terms of earnings losses and job-finding difficulties. The results shown in Figure 5 indicate a clear and persistent negative impact on earnings and employment probability for all worker types, regardless of their pre-pandemic characteristics. Overall, this highlights the broad and indiscriminate nature of the shock.

FIGURE 5. Job Loss Effects by Worker Types

A. Earnings

B. Probability of being employed



Notes: The panel shows the job loss effects on earnings and change in the probability of being employed for workers who suffered a job displacement during the pandemic, relative to stayers, jointly with a 95% confidence interval estimated with clustered standard errors at the individual worker level.

Our results speak closely to the existing literature on the compositional changes in the pool of unemployed over the business cycle. We observe that workers with high abilities, better job search skills, and longer-term employment histories were similarly impacted in terms of earnings and job loss as compared to other worker types. This is consistent with Mueller (2017), which demonstrates that during recessions, the pool of unemployed individuals tends to skew toward workers who previously earned high wages (in our case, worker type A). While Mueller (2017) suggests that this shift is attributable to the high cyclicality of job separations for high-wage workers, our results could also be due to the unprecedented scale of the COVID-19 shock. Further research is necessary to gain a better understanding of these dynamics and to characterize the post-pandemic labor market recovery.

5.2. Reallocation Dynamics

In this section, we delve into the dynamics of reallocation, with a specific focus on occupational transition. Table 5 provides a comprehensive overview of how displaced workers from each category were sorted into different occupations before the job separation. Although a significant proportion of displaced workers are concentrated in the lowest skilled occupations, there is also considerable dispersion even among higher skilled occupations. Furthermore, job displacements from higher skilled occupations are relatively more prevalent in Type A compared to other types.

TABLE 5. Occupational Distribution by Worker Types

	Displaced COVID-19			**All**		
	Type A	**Type B**	**Type C**	**Type A**	**Type B**	**Type C**
Managers & professionals	5.25	2.45	1.05	20.7	5.9	8.88
Technicians & associate professionals	23.65	16.72	22.48	26.21	18.94	20.17
Clerical support workers	23.6	18.99	20.15	14.28	17.75	18.63
Service, skilled agricultural & craft	14.59	25.06	17.65	15.94	18.99	20.73
Plant operators and assemblers	5.83	7.86	6.2	6.29	9.08	6.76
Elementary occupations	27.07	28.92	32.47	16.58	29.35	24.83

Notes: Table show the distribution of workers across occupations within each worker type. Occupation classification using ISCO-08 codes. Managers & professionals: ISCO Major groups 1 and 2 with skill level 3 and 4, with 4 the highest skilled group. Technicians & associate professionals: Group 3 with skill level 3. Clerical Support Workers: Group 4 with skill level 2. Service, skilled agricultural: Groups 5 (services and sales), 6 (Skilled agricultural, forestry, fishery) and 7 (crafts and related trades), with skill level 2. Plant operators and assemblers: Group 8 with skill level 2. Elementary occupations: Group 9 with skill level 1.

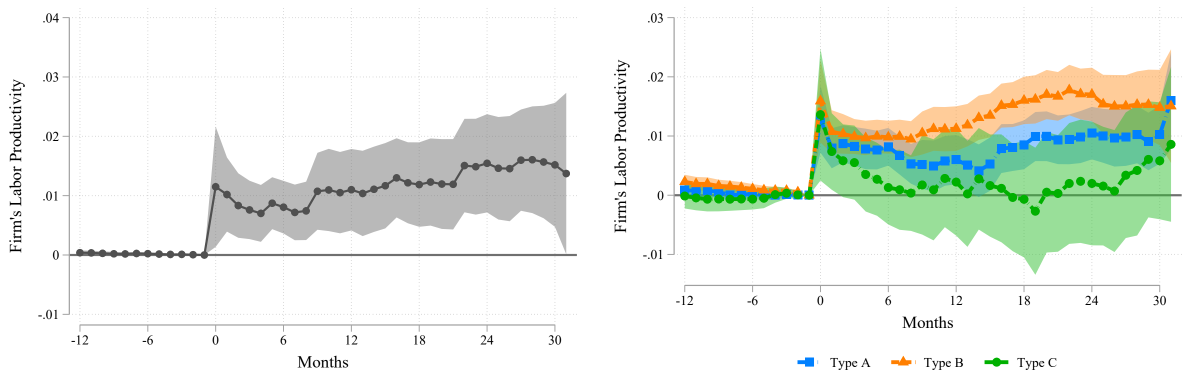
Displaced workers move to more productive firms. According to Figure 6, we observe that workers who lost their job during the pandemic tend to reallocate to firms that *ex-ante* had higher productivity levels compared to the firms they were previously employed at. This suggests that despite the negative effects of displacement, workers are able to transition and contribute to relatively more productive firms, despite the adverse effect on their earnings. This result aligns with the empirical evidence that during recessions, less productive firms exit the market, causing the lower end of the productivity distribution to shrink (Haltiwanger 2022).

Figure 6 further reveals that the aggregate transition dynamics are mostly explained by worker types A and B. This suggests that these workers, who have higher ability parameters (see Table 1) and more stable job histories, are able to transition to better firms despite the adverse effects of displacement. In contrast, worker type C showed no statistically significant transition. This could be due to a combination of factors, such as lower levels of ability or less favorable job market conditions for this worker type. Overall, our findings highlight the importance of considering unobserved heterogeneity in analyzing the reallocation dynamics of displaced workers and their potential impact on firm productivity.

FIGURE 6. Reallocation Dynamics: Firm's Ex-ante Labor Productivity

A. Earnings

B. By worker type



Notes: The panel shows the reallocation dynamics for workers displaced at month $m = 0$ during the pandemic. The firm's labor productivity is defined as real value-added per worker and it is measured ex-ante the pandemic as the average of 2010-2019 firm-level information. Figures show a 95% confidence interval estimated with clustered standard errors at the individual worker level.

The results of our study, which show workers moving to firms with higher productivity levels than their previous employer, do not necessarily indicate that the new firms have become more productive after the COVID-19 pandemic. It is also not necessarily the case that the destination firm has become more productive due to this reallocation of workers. Further research would be needed to establish the impact of this worker reallocation on the productivity of the new firms.

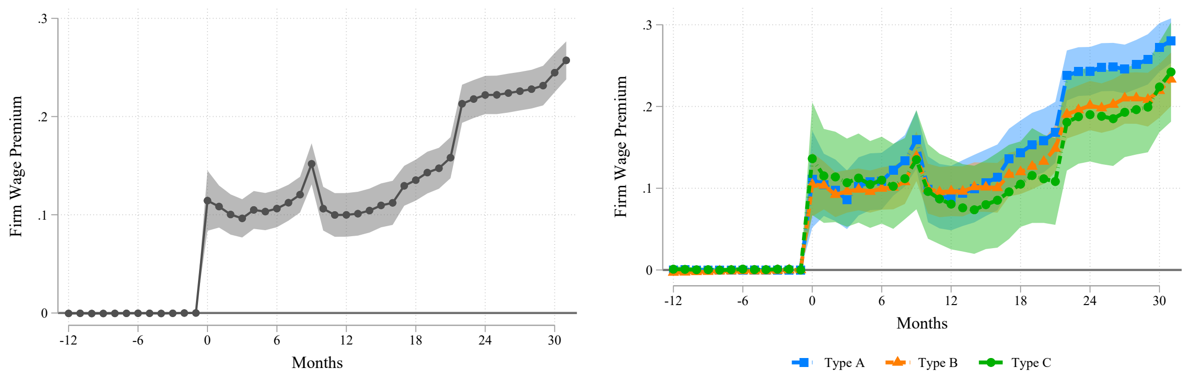
Displaced workers move to higher-paying firms. Our research findings indicate that displaced workers during the pandemic tend to move to firms that *ex-ante* offer higher wage premiums[23] compared to their previous employers (see Figure 7). This implies that they are relocating to firms that pay more than other firms in the same industry or job category. Additionally, this pattern discards the fact that the calculated earning losses are determined by a shift of workers to low-productivity firms. Despite differences in abilities, job tenure, and unemployment history, all worker types seem to show similar trends regarding the kinds of firms they move to and the wage premiums connected with those firms. This suggests that the observed reallocation dynamics may be driven by broader market forces rather than individual characteristics.

[23]Figure A3 computes the same exercise but using the firm-level average wage paid to workers.

FIGURE 7. Reallocation Dynamics: Firm's Wage Premium

A. All workers

B. By worker type

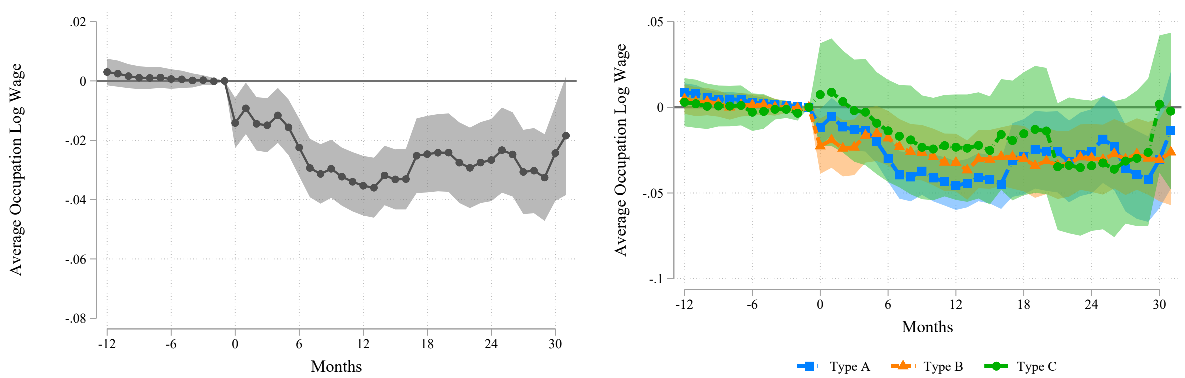


Notes: The panel shows the reallocation dynamics for workers displaced at month $m = 0$ during the pandemic. The firm's wage premium is measured as the firm fixed effect in the AKM model, and it is computed ex-ante the pandemic as the average of 2010-2019 firm-level information. Figures show a 95% confidence interval estimated with clustered standard errors at the individual worker level.

Our results differ from those of Brandily et al. (2022), Schmieder et al. (2022), and Bertheau et al. (2022), who found that destination firms tend to be more productive but pay a *lower* premium. Hence, this research links the earning losses to (i) changes in employer characteristics after the layoff and (ii) a decline in bargaining power for workers, rather than difficulties in accessing jobs at productive firms. In our case, workers moving to more productive and higher-paying firms may appear contradictory. However, this pattern has also been observed in previous studies, and literature has attempted to explain it. Moscarini and Postel-Vinay (2018) propose that during a recession, the job market becomes highly competitive as many workers are competing for a limited number of jobs. As a result, displaced workers may be forced to accept lower-paying positions in order to secure employment, but these positions may be with firms that have higher productivity levels, offering better opportunities for wage growth and career advancement in the long run. While both explanations are not mutually exclusive, further research is needed to determine which one is relatively more important, as they have different policy implications.

Displaced workers move to lower-paying occupations. To gain insight into the causes of earnings decline after a job loss, we study whether displaced workers moved to *ex-ante* lower-paying occupations. We want to provide a comprehensive picture of the reallocation process, including the occupations workers move to and the potential heterogeneity across worker types. Figure 8A shows that workers who have experienced job loss during the pandemic are relocating to occupations with lower wages. This result provides evidence that the negative earnings effects experienced by displaced workers are not solely due to a decrease in bargaining power but also due to a shift towards lower-paying occupations.

Our analysis further suggests that worker types A and B are the ones who primarily determine the aggregate dynamics, as illustrated in Figure 8B. Given that worker types A and B are workers with relatively higher skills, it is possible that they were previously higher up in the job ladder and thus were earning a higher wage. However, due to the competitive job market during the pandemic, these workers may have had to accept lower-paying positions in order to secure employment, which has resulted in them moving to lower-paying occupations.



A. All workers

B. By worker type

FIGURE 8. Reallocation towards lower-paying occupations

Notes: The panel shows the reallocation dynamics for workers displaced at month $m = 0$ during the pandemic. We compute the within-occupation average wage prior to the pandemic as the average of 2010-2019 occupation-level information. Figures show a 95% confidence interval estimated with clustered standard errors at the individual worker level.

Displaced workers are not initially moving to remote job occupations. Figure 9 indicates that displaced workers are accepting positions that are less likely to be impacted by remote work arrangements[24]. This is likely due to a variety of reasons, including the need for workers to secure employment quickly after a job loss, the limited availability of remote jobs, and the lack of prior experience in remote work. Furthermore, displaced

[24]We follow Dingel and Neiman (2020) to classify occupations according to jobs that can be done from home, using four-digit occupation codes. For instance, office jobs can be done remotely, but occupations in agriculture must be performed on-site.

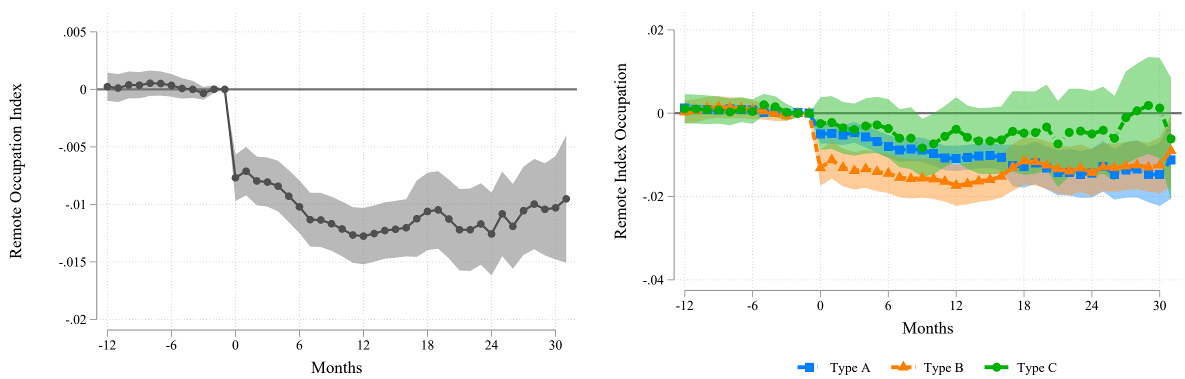
workers moving to non-remote jobs suggests that, in our case, the shift towards remote work is likely to be an intensive margin change, i.e., employed workers opting to work from home rather than those entering the job market. Despite our findings, it is important to note that the level of unemployment during the study period was still higher than pre-pandemic levels, unlike the U.S. labor market, which saw a sharp decrease in unemployment rates and exhibited a tight labor market during 2022 (Michaillat and Saez 2021).

Our analysis of worker heterogeneity reveals that occupational switching is particularly pronounced for worker types A and B. According to Table 1, these two worker types are characterized by higher ability, greater job stability, and more efficient job search outcomes. However, future research must keep a close eye on the occupational reallocation dynamics as the labor market continues its recovery post-pandemic. This will help to detect any changes in the patterns of reallocation that may occur as the market stabilizes.

FIGURE 9. Reallocation towards remote occupations

A. All workers

B. By worker type



Notes: The panel shows the reallocation dynamics for workers displaced at month $m = 0$ during the pandemic. We compute the remote index following Dingel and Neiman (2020). Figures show a 95% confidence interval estimated with clustered standard errors at the individual worker level.

6. Discussion

Our paper offers a valuable but partial perspective on the adjusting dynamics of the labor market in response to the pandemic disruption. Despite this, our results highlight crucial policy implications and avenues for future research. Further investigation is needed to deepen our understanding of the impact of the pandemic on the labor market and inform the development of effective policy responses.

Future research should aim to structurally measure the costs associated with job loss and assess the impact of the pandemic on the labor market. This analysis should include an in-depth examination of firm dynamics, with a focus on how the pandemic and the subsequent recovery have affected the skill allocation of workers to jobs. Moreover, there is still limited information on the firm-level effects of the worker reallocation process induced by COVID-19. Incorporating these considerations would provide a more comprehensive understanding of the macroeconomic consequences of job loss and inform effective policy responses to mitigate its negative effects.

The findings of this study highlight the importance of quickly re-employing workers to jump-start the process of finding a good match, especially during a recession such as the COVID-19 pandemic. Given the substantial earnings losses and the slow recovery of earnings among displaced workers, policymakers should consider targeted interventions to mitigate the negative effects of job loss on workers' earnings and employment prospects. This could include programs, hiring tax credits, or subsidies to stimulate labor demand and support worker retraining and skill development. Additionally, as our study highlights the role of occupational switching in determining wage losses, policies aimed at promoting job mobility and reducing occupational rigidity could be beneficial in helping workers find higher-paying jobs that match their skills. Finally, by establishing and enhancing the generosity of unemployment insurance (UI), out-of-work individuals may be assisted in finding better matches when they are non-employed, which should result in more stable post-separation employment.

Our results are similar to the outcomes of Cortés and Forsythe (2023) for the case of the United States. They find that the effect of COVID was heterogeneous among different groups of the population. Hispanics and non-white workers were more affected relative to white workers. These groups with a higher incidence of job loss are also characterized by a lower level of education. This coincides with our findings, specifically the fact that less qualified workers find it more difficult to get their jobs back. The authors conclude that the pandemic exacerbated inequalities that existed before the pandemic.

In future research, it is crucial to incorporate information on the informal sector to obtain a more comprehensive understanding of the earning consequences of job loss and to identify reallocation dynamics with greater precision. The informal sector plays a significant role in many economies, particularly in developing countries. By including data and analyses that capture the informal sector's dynamics, we can gain insights into the full extent of the impact of job loss on workers' earnings and the subsequent reallocation processes.

7. Conclusions

This paper provides valuable insights into the economic consequences of job displacement for workers and firms. By using a rich dataset that links employer-employee information, we identify three distinct worker types based on unobserved heterogeneity and examine the impact of job displacement on their earnings. Our results reveal persistent earning losses for displaced workers, especially during economic recessions, such as the recent pandemic. Additionally, we find that job finding, or the extensive margin, plays a crucial role in explaining these earning losses. We further document that displaced workers during the pandemic are moving to more productive and higher-paying firms. The findings emphasize the importance of new job characteristics in explaining earning losses and suggest that future research should focus on the productivity-enhancing nature of labor reallocation and the occupational dynamics in the aftermath of downsizing events.

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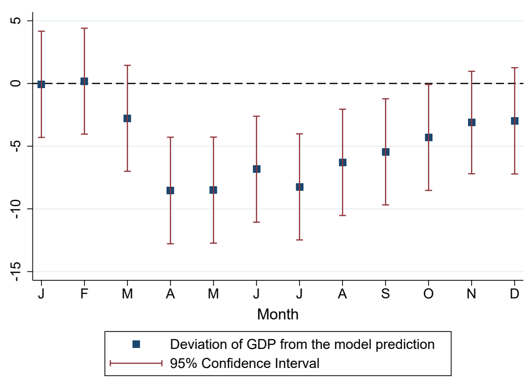
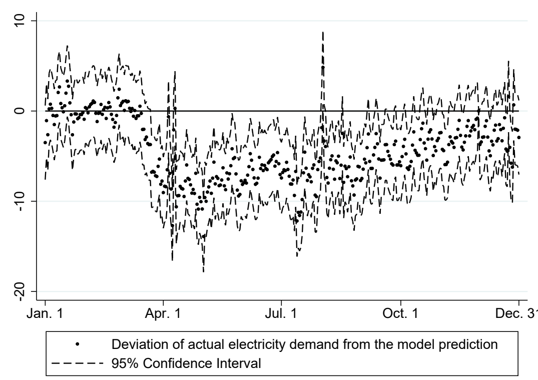
Appendix

FIGURE A1. Real GDP and Electricity Demand Dynamics During 2020

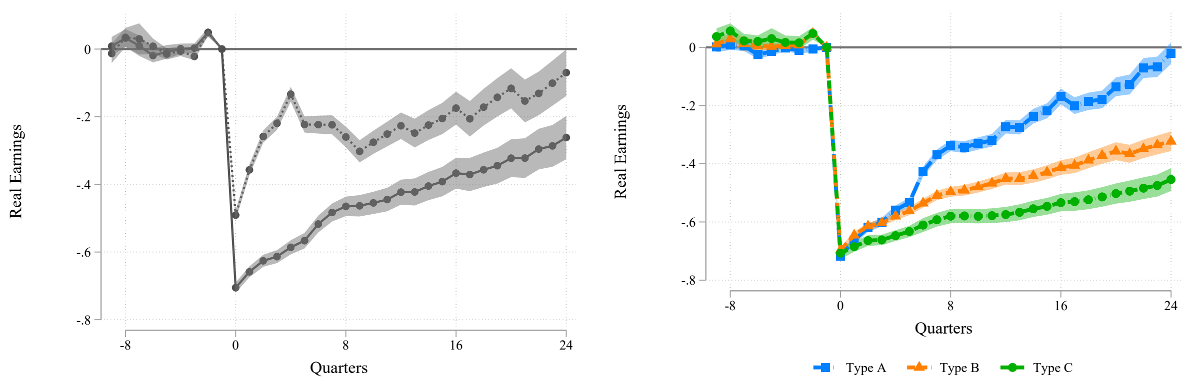




Notes: The graphs show the real GDP and electricity consumption dynamics for Costa Rica relative to pre-pandemic levels. Source: Barquero-Romero et al. (2022) and Central Bank of Costa Rica.

FIGURE A2. Earnings effect for displaced workers (Prior to 2020, excluding zeros)

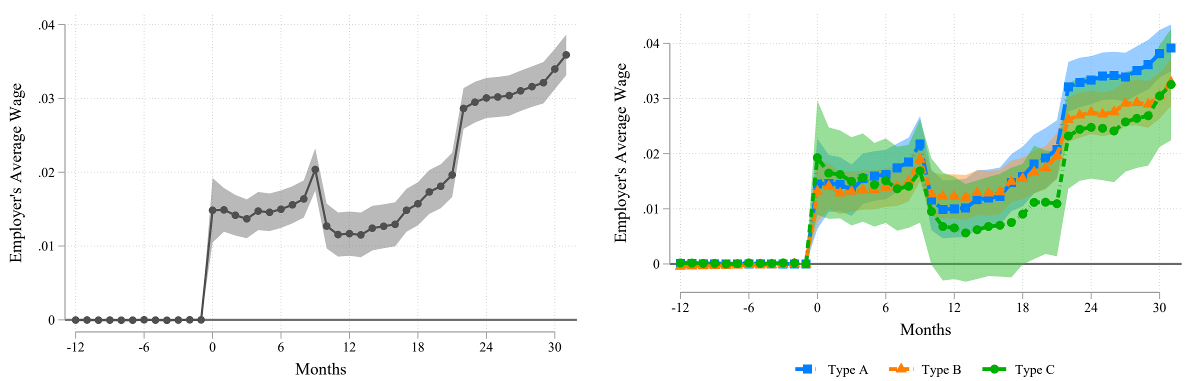
A. All workers B. By worker type



Notes: The panel shows the earnings effects for workers who suffered a job displacement at quarter $q = 0$ (2009-2019), relative to stayers and conditional on being employed. The 95% confidence interval is estimated with clustered standard errors at the individual worker level.

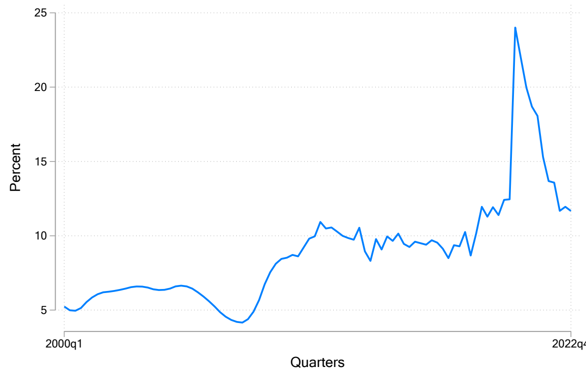
FIGURE A3. Reallocation Dynamics: Firm Ex-ante Average Wage

A. All workers B. By worker type



Notes: The panel shows the reallocation dynamics for workers displaced at month $m = 0$ during the pandemic. The firm average wage is estimated as the simple average of monthly wages paid by the establishment between 2010 and 2019. Figures show a 95% confidence interval estimated with clustered standard errors at the individual worker level.

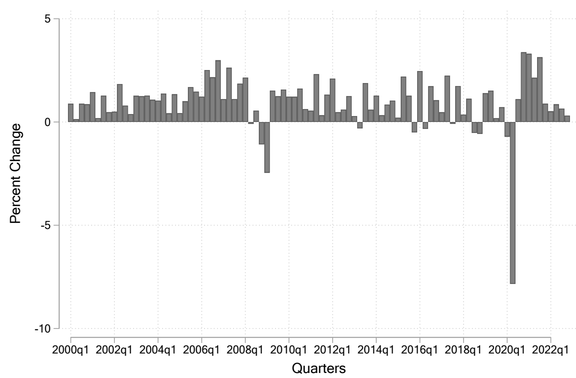
FIGURE A4. Unemployment Rate in Costa Rica. Period 2000-2022



Source: National Institute of Statistics and Census (INEC).

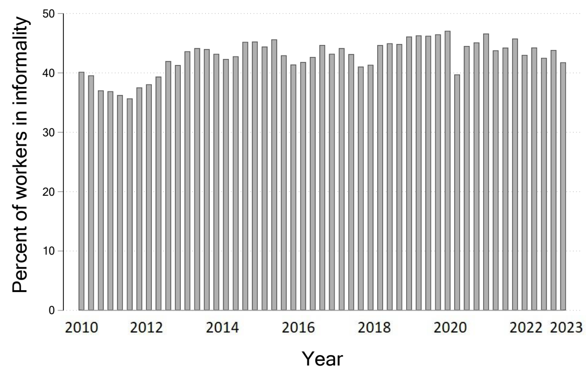
FIGURE A5.

Quarterly Real GDP Growth Rate. Seasonally Adjusted



Source: Central Bank of Costa Rica.

FIGURE A6. Informality in the labor market. Percent of total workers. Period 2010-2023



Source: National Institute of Statistics and Census (INEC)