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Routine-biased technological change and employee outcomes after mass layoffs: evidence from Brazil

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Abstract

We investigate the impact of "routinization" on the labor outcomes of displaced workers. We use a rich Brazilian panel dataset and an occupation-task mapping to examine the effect of job displacement in different groups, classified according to their tasks. Our main result is that following a layoff, workers previously employed in routine-intensive occupations suffer a more significant decline in wages and more extended periods of unemployment. As expected, job displacement has a negative and lasting impact on wages. Still, workers in routine-intensive occupations are more impacted than those in non-routine occupations in terms of wages (an increase of one point in the routine-intensity index results in a further decline of 2 percent in workers' relative wages) and employment. Furthermore, our results indicate that workers in routine-intensive occupations are more likely to change occupations after the shock, and those who do not switch occupational fields suffer a more significant decline in wages. Lastly, even though the loss of employer-specific wage premiums explains 13 percent of displaced workers' drop in wages, it does not explain routine-intensive workers' more substantial losses.

JEL: J24, J63, O54

Keywords: Routine intensity; Job displacement; Mass layoffs; Occupational mobility; Brazil

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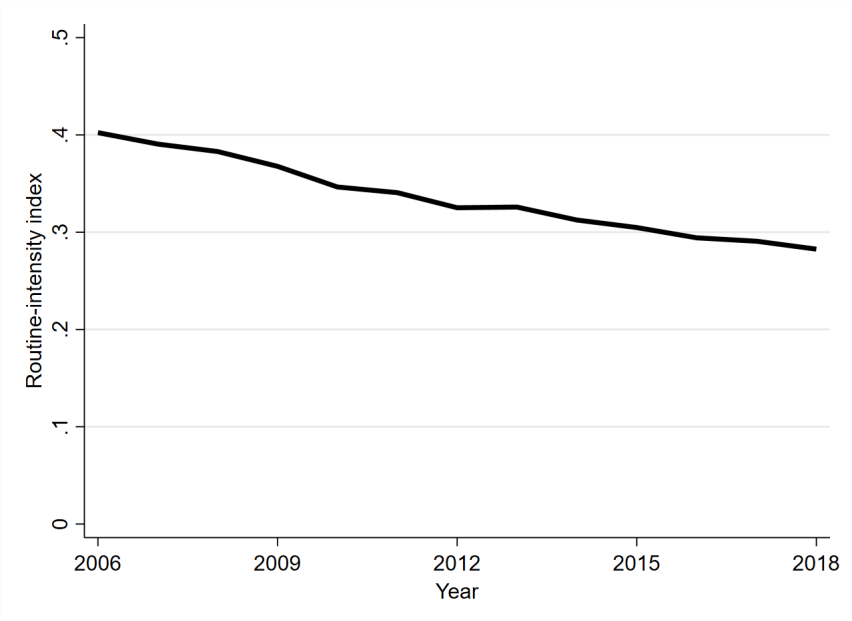
1 Introduction

Creative destruction has been referred to as the engine of modern economic growth (Aghion et al., 2021; Aghion and Howitt, 1992; Romer, 1990; Schumpeter, 1942) and a key driver of productivity differences across countries (Comin and Hobijn, 2010; Comin and Mestieri, 2018; Easterly and Levine, 2001). Central to the process of creative destruction is technological change and how resources are reallocated to firms that are able to disrupt markets with new technologies. The effects of this process of technological change in labor markets, however, are not homogeneous. In recent decades, a significant amount of evidence has documented the increasing polarization and inequality in the labor markets, especially in developed economies, with the share of high-skill, high-wage, and low-skill, low-wage occupations growing relative to those in the middle of the distribution. This "hollowing out" of the middle of the wage distribution has been commonly associated with automation and changes in the task requirements in production. The routine-biased technological change (RBTC) hypothesis argues that computers and robots have diminished the demand for routine, repetitive tasks in production, which more commonly concentrates among middle-earning workers (Acemoglu and Autor, 2011; Autor et al., 2003; Goos et al., 2009).

The phenomenon of job polarization and its association with technology adoption has been largely tested and confirmed in the context of advanced economies (see, for instance Acemoglu and Autor, 2011; Autor et al., 2003; de Vries et al., 2020; Dustmann et al., 2009; Fonseca et al., 2018; Goos et al., 2009; Michaels et al., 2014; Spitz-Oener, 2006). In contrast, the picture is less evident in developing economies, where indications of job polarization are considerably weaker. Maloney and Molina (2019) and Das and Hilgenstock (2018) find little evidence of labor market polarization or increased inequality in developing countries, either in absolute levels of employment or share of the workforce. Gasparini et al. (2021) find similar results for Latin America's six largest economies, showing no evidence for polarization in the labor market (see Martins-Neto et al. (2021) for a literature review of job polarization in developing economies).

Figure 1: Evolution of routine intensity in Brazil



Source: Own elaboration. The routine-intensity (RTI) index is based on Goos et al. (2014). The following occupations are dropped: legislators and senior officials (ISCO 11); teaching professionals and teaching associate professionals (ISCO 23 and 33); skilled agricultural and fishery workers (ISCO 61); and agricultural, fishery and related laborers (ISCO 92).

Despite this lack of apparent "hollowing out" in the middle of the distribution consistent with job polarization, the empirical literature suggests a decline in routine intensity across countries and that technological progress has diminished the demand for routine-intensive occupations in developing countries – which is a crucial precondition for polarization. For instance, Gasparini et al. (2021) shows a decline in job growth in routine-intensive occupations in Latin America's largest economies, and Reijnders and de Vries (2018) document an increasing share of non-routine occupations in developing countries' labor forces. In Brazil, Firpo et al. (2021) shows that despite the lack of job polarization, the routine intensity of occupations declined considerably. Figure 1 highlights this result, displaying the decline of routine tasks in Brazil from 2006 to 2018.

With or without the polarization in labor outcomes, a critical question for developing countries is the implications of this decline in routine-intensive occupations in labor outcomes, where the extent of job insecurity and informality is larger, and wages are critical for

the income distribution. It remains unclear whether workers employed in routine-intensive occupations are already facing the adverse effects of this process, which groups of workers are experiencing the adverse effects more strongly, and how large this effect is. So far, most of the studies in developing economies have focused primarily on aggregate outcomes such as changes in occupational employment and the extent of job polarization, thus failing to observe workers' transitions across occupations and the effects on individuals' wages and unemployment duration. This paper attempts to fill this gap in the literature.

One challenge when measuring the impact of exogenous changes in the demand for routine tasks on labor outcomes is the fact that it is difficult to disentangle the effects of "routinization" from endogenous decisions and responses from workers. Therefore, we employ an event-study approach (Blien et al., 2021; Couch and Placzek, 2010; Jacobson et al., 1993; Raposo et al., 2019), treating mass layoffs as an external shock. Specifically, to better identify the role of "routinization" on employment outcomes, we use this exogenous sizable negative shock - mass layoffs - and explore how re-employment probabilities and wage dynamics vary by the level of occupations' routine intensity.

Our study contributes to the labor economics literature on outcomes across displaced workers. Following the seminal work of Jacobson et al. (1993), studies have found that workers face a significant decline in salaries after displacements, with sustained effects ranging from 3% to 25% depending on the region and methodology (see, for instance Couch and Placzek, 2010; Eliason and Storrie, 2006; Hijzen et al., 2010; Huttunen et al., 2006; Ichino et al., 2017; Kaplan et al., 2005; Menezes-Filho, 2004; Raposo et al., 2019). Using Brazil's matched employer-employee data set (RAIS) in the mid-1990s, Menezes-Filho (2004)'s pioneering paper finds that high-tenure workers suffer a long-term loss in monthly wages of about 20% per year. Saltiel (2018) examined the Brazilian labor market outcomes over 2002-2012, with similar results to Menezes-Filho (2004): affected workers suffer annual earnings losses exceeding 15-20%, and the effect persists through the medium term. We contribute to this literature by examining a number of heterogeneities across workers' groups, while

also exploring a larger and more recent sample. For instance, Menezes-Filho (2004) focuses on male workers in the state of São Paulo and Saltiel (2018) includes only displaced workers that do not face longer periods of unemployment, thus underestimating the impacts of displacement. In addition, following (see, for instance, Bertheau et al., 2022; Fallick et al., 2021; Lachowska et al., 2020), we estimate the loss of employer-specific wage premiums.

We also contribute to the recent literature in labor economics that has looked into the effects of technological change and occupational differences across displaced workers. Bessen et al. (2019) explore the direct impact of technology adoption at the firm level on workers' probability of separation from their current jobs and their future labor prospects. They find that automation at the firms increases workers' separation risk and that displaced workers are more likely to work fewer days in the years to come. However, differently from our analysis, the authors do not explore differences between workers previously employed in different occupations. Goos et al. (2021) examined survey data of workers previously employed in a large Belgian establishment in the automotive sector. After the plant closed and in line with the RBTC hypothesis, workers in routine-intensive occupations were less likely to find a job 1,5 years after the event. Additionally, for those workers who could find a job, the non-routine content of job tasks was higher, wages were lower, and permanent jobs were less frequent. In line with our results, they find a more significant impact on wages and employment for displaced workers previously employed in routine-intensive occupations (compared to their non-routine-intensive counterparts). However, the authors concentrate the analysis on a case study of one firm, which raises questions about possible selection bias, endogeneity, and generalizability of the results. In turn, our work is closest to a recent analysis of German displaced workers. Using data from 1980 to 2010, Blien et al. (2021) test whether workers in routine intensive occupations are disproportionately affected by job separation. They find evidence that workers in routine occupations undergo more considerable and more persistent wage losses and that the difference compared to non-routine workers has increased over time.

An important contribution of this study is to examine the impact of RBTC in the context

of a middle-income country such as Brazil. Brazil presents an interesting case for comparison for various reasons besides the previously-mentioned weaker evidence of job polarization. First, labor market institutions have exacerbated market frictions and mismatches in the labor market (Ulyssea, 2010). Second, minimum wage policies have helped decrease wage inequality significantly in the last decade, and the wage gap between low and high skilled workers narrowed significantly (Alvarez et al., 2018; Firpo et al., 2021). Third, productivity growth has remained stagnant, suggesting a lack of significant technological change. Fourth, in many developed economies, participation in GVCs spurred "routinization". However, Brazil has remained relatively isolated from global offshoring, with low participation in GVCs and services trade due to restrictive trade policies and lack of skills. This combination of labor institutions and the lack of internationalization of Brazilian companies makes the country a very interesting case study to explore the impact of "routinization."

An additional important contribution of the paper is the heterogeneity analysis, including the differences between female and male workers, long- and short-tenured individuals, and firms' size. These dimensions seem to play a critical role in explaining the adverse effects of displacement. Also, we explore some possible mechanisms explaining the larger decline in wages, especially the roles of demand, job switchers, and firms' heterogeneity.

To advance some of the main findings, we observe a significant and long-lasting negative impact of job displacement on workers' wages and employment. Based on Jacobson et al. (1993)'s methodology, the results show a large and statistically significant wage loss associated with job displacement. Workers in the treated arm see their relative monthly earnings decline over 20% in the year following the layoff and up to 5% five years after the event. The shock also affects workers' relative employment, as displaced individuals work over 15% less in $t+1$ and 3% less five years after the layoff. In addition, we find that the loss of employer-specific wage premiums explains 13% of the decline in wages for the treated group. Following the initial results, we test for differences between routine and non-routine workers. First, we find strong evidence that workers in routine-intensive occupations are more impacted than

those in non-routine occupations. An increase of one point in the routine-intensity index results in a further decline of 2% in workers' relative wages and an increase of 1% in the chance of unemployment. Second, we explore the heterogeneity in our results and find a more significant decline in wages for male, less educated, and long-tenured individuals in routine intensive occupations. In addition, our findings suggest that the negative impact is larger in sectors with a larger decline in the demand for routine tasks. Third, we show that workers in routine-intensive occupations are more likely to change occupations after the shock. However, those unable to switch fields experience a more significant decline in wages. Lastly, we find that the loss of employer-specific wage premiums does not explain routine-intensive workers' more substantial reduction in wages.

The paper is organized as follows. The following section describes the data sources and the definition of involuntary displacement events. Section 3 describes the empirical strategy. Section 4 estimates the impact of job displacement in Brazil and examines the heterogeneity across occupational groups, especially routine-intensive occupations. Section 5 examines the heterogeneity across occupational groups and investigates the importance of the demand for routine occupations in explaining labor outcomes from displacement; including differences across sectors, between occupational switchers and non-switchers, and the role of firms' heterogeneity. The last section concludes.

2 Data and sample construction

2.1 Data

To estimate the impact of displacement on wages in Brazil, we use the RAIS database (Relação Anual de Informações Sociais) from 2006 to 2018. This is an administrative database from the Brazilian Ministry of Economy considered a high-quality census of the Brazilian formal labor market. The census includes all establishments nationwide with at least one registered worker — even though we carry our analysis at the establishment level, we

refer to firms and establishments interchangeably. The data includes over 30 million employees per year, matched with firm information, including location and industry, and workers' gender, age, education, employment status, wages, type of contract, tenure, and hiring date. RAIS reports compensation as the monthly average wage received by each worker (including regular salary payments, holiday bonuses, performance-based and commission bonuses, tips, and profit-sharing agreements).

We restrict our analysis to employees in private establishments, and focus on workers displaced in 2009-2013 due to establishments' closure or mass layoffs (see definition below). We observe workers' outputs three years before displacement and five years following the event. This period includes both a moment of fast national economic growth (2009-2012) and a period of economic stagnation with recessions in 2015 and 2016 when GDP dropped by 3.5% and 3.2%, respectively. Thus, for workers displaced in 2009, the booming labor market should have facilitated their reinsertion. In contrast, for workers displaced in 2013, the entire period following the shock is a period of wage stagnation and increased unemployment.

The database includes information on each worker's occupation, coded according to the Brazilian Code of Occupations (CBO). To measure the task content of occupations, we follow Goos et al. (2014), who mapped the routine intensity index (RTI) to ISCO-88 occupations. This RTI measure is based on Autor et al. (2003) and combines five task measures from the US Dictionary of Occupational Titles (DOT) to produce three aggregate measures: Manual, Routine, and Abstract task measures.[1] The Routine Task Intensity (RTI) index takes the difference between the log of Routine tasks and the sum of the log of Abstract and the log of Manual tasks.[2] We map these occupations to the Brazilian Code of Occupations. Table 1

[1]Specifically, Manual tasks relate to the occupation's demand for "eye-hand-foot coordination" (EYE-HAND), and Abstract tasks refer to the simple average of occupations' managerial and interactive tasks (DCP) and mathematical and formal reasoning requirements (GED-MATH). In contrast, the Routine task measure is a simple average of the following variables: "set limits, tolerances and standards" (STS), which measures an occupation's demand for routine cognitive tasks; and "finger dexterity" (FINGDEX), which measures an occupation's use of routine motor tasks.

[2]Even though the task content of occupations may differ across countries (see, for instance, Lewandowski et al. (2019)), we assume that the ranking of occupations in terms of routine intensity may not vary significantly across countries.

describes the occupations ranked by the level of routine tasks; RTI is highest at 2.24 for office clerks (41) and lowest at -1.52 for managers of small enterprises (13).

Table 1: Routine-intensity by occupation

Occupation	**RTI Index**
Managers of small enterprises	-1,52
Drivers and mobile plant operators	-1,50
Life science and health professionals	-1,00
Physical, mathematical and engineering professionals	-0,82
Corporate managers	-0,75
Other professionals	-0,73
Personal and protective service workers	-0,60
Other associate professionals	-0,44
Physical, mathematical and engineering associate professionals	-0,40
Life science and health associate professionals	-0,33
Extraction and building trades workers	-0,19
Sales and service elementary occupations	0,03
Models, salespersons and demonstrators	0,05
Stationary plant and related operators	0,32
Laborers in mining, construction, manufacturing and transport	0,45
Metal, machinery and related trade work	0,46
Machine operators and assemblers	0,49
Other craft and related trade workers	1,24
Customer service clerks	1,41
Precision, handicraft, craft printing and related trade workers	1,59
Office clerks	2,24

Source: Own elaboration. The following occupations are dropped: legislators and senior officials (ISCO 11); teaching professionals and teaching associate professionals (ISCO 23 and 33); skilled agricultural and fishery workers (ISCO 61); and agricultural, fishery and related laborers (ISCO 92). The routine-intensity (RTI) index is based on Goos et al. (2014).

2.2 Sample construction and matching

Our identification strategy rests in examining the impacts of a sudden exogenous shock on workers' career prospects. Specifically, we look at individuals displaced due to establishments' closures or mass layoffs. Yet, the RAIS database does not carry information on the year an establishment closes. Instead, as is commonly done in the literature, we use the establishment's unique identifier and define exits when the employer identifier ceases to exist (see, for instance Schwerdt et al., 2010). For example, we assign an establishment in 2010 as closed if it appears in our database in the years preceding 2010 and disappears afterward.

Furthermore, we define mass layoffs when 30% or more workers are laid off between $t-1$ and t. We impose an additional restriction to avoid capturing seasonal changes in employment and exclude cases in which employment fluctuated by 20% in the two years before the mass layoff, or the firm size went above 150% compared to the year of the layoff. To put it simply, we exclude cases in which the trend was already perceived in the years before or when employment recovers in the years following. In addition, some of these events might not be actual closures. Establishments can change their identifier in time or spin-off into different companies. We impose an additional restriction to capture these cases and exclude cases in which more than 50% of the employees continue under a new employer identifier.[3]

As it is commonly done in the mass layoff literature, we restrict our sample to full-time prime-age workers, focusing on individuals older than 25 or younger than 50 years in the first year of analysis (for instance, for workers displaced in 2010, the first year of study is 2007). The reason to restrict workers' age is that younger workers can be working as apprentices or interns, while older workers can opt to leave the market and retire. We also restrict establishments' size, focusing on establishments with at least 30 employees in the first year before the event. We also limited our sample to one observation per worker-year by choosing the highest-paying in any given year. We also excluded observations where the data were miscoded or missing. Furthermore, we impose that displaced individuals work in the same company for at least three years before the layoff. By setting this restriction, we focus on workers in stable positions, who would have likely continued had the closure not occurred.

To estimate the effects of displacement, we include a control group with workers who continue to work at firms that had no mass layoff during the period of analysis. For this control group, we also impose at least three years of tenure before the "potential displacement". In our analysis, displacement affects workers at different times (i.e. there is variation in treatment timing, Roth et al., 2022), and therefore to ensure the validity of the difference-

[3]One downside in using RAIS database is that it only covers formal workers. In this scenario, if a worker becomes unemployed or moves to the informal sector, which comprises about 40% of the Brazilian labor market, we will not be able to track her. Therefore, transitions from the formal to the informal are not captured in our analysis, being thus treated as movements to unemployment.

in-difference setup, we guarantee that the control group includes only workers that will never be part of a mass layoff in subsequent years (de Chaisemartin and D'Haultfœuille, 2020), hence avoiding the problem of "forbidden" comparisons (Roth et al., 2022). However, other than that, we do not include any additional restriction in the years following the "potential displacement". In other words, we aim to compare long-tenured workers with a control group of individuals that are as similar as possible in all domains, except for the displacement.

To identify a set of control workers, we implement a two-stage matching procedure in $t-2$. First, we perform exact matching on workers' occupations (2-digits), gender, and on Brazil's 27 states. In the second step, we implement the coarsened exact matching (CEM) algorithm (Iacus et al., 2012). Then, we apply the CEM algorithm on a series of covariates at both worker-level (wage, wage growth, age, tenure, and education) and establishment-level (number of workers, average salary, and sector (2-digits)). By including workers' wage growth, we ensure that workers display similar trends in salaries before the shock, a key identification restriction of the difference-in-difference estimator.

This matching procedure yields a sample of about 135 thousand treated workers and 135 thousand workers in the control group. Table 2 shows the descriptive statistics of various workers' and establishments' characteristics for workers in the treatment and control arms two years before the layoff. The last column shows the difference between the means. Workers in the control group earn slightly more than treated individuals, although the difference is not statistically significant. Displaced workers have similar age and tenure as the control group and work in larger firms. In contrast, firms' average wage is not statistically different between displaced and control workers. As expected, most individuals in our sample are placed in the Southeast of Brazil. This is the most populous region in the country and includes the state of São Paulo, the wealthiest state in Brazil. In addition, about one-third is employed in the manufacturing sector, and about one-third of workers in the sample are female. Less than 10% of our sample has a college degree. In contrast, 49% has only a high-school diploma (Figure A1 shows the histogram of the routine-intensity index for the

matched sample).

Table 2: Comparison of treated and control groups after matching

	Control		Treated		
	Mean	Standard Deviation	Mean	Standard Deviation	Difference
Wage	1478	1498.46	1487	1508.68	9.442
Wage Growth	.11	0.26	.1	0.26	-0.005***
Worker's age	35	6.34	35	6.34	-0.002
Gender	.32	0.47	.32	0.47	—
Illiterate or primary school	.026	0.16	.026	0.16	0.000
Primary school graduate	.16	0.37	.16	0.37	0.000
Middle school graduate	.24	0.43	.24	0.43	-0.000
High-school graduate	.49	0.50	.49	0.50	-0.000
College degree	.081	0.27	.081	0.27	0.000
Tenure	63	43.24	63	43.25	-0.282**
Size (30-49)	.15	0.35	.12	0.33	-0.025***
Size (50 - 99)	.17	0.38	.17	0.37	-0.008*
Size (100-499)	.38	0.49	.4	0.49	0.011
Size (500+)	.29	0.46	.32	0.46	0.022***
Firm's average wage	1533	1201.26	1548	1225.56	15.328
Agriculture and Extractive	.025	0.16	.025	0.15	-0.001
Manufacturing	.36	0.48	.36	0.48	-0.000
Services	.61	0.49	.61	0.49	0.001
North	.02	0.14	.02	0.14	—
Northeast	.12	0.32	.12	0.32	—
Southeast	.71	0.46	.71	0.46	—
South	.12	0.33	.12	0.33	—
Central-West	.036	0.19	.036	0.19	—
Observations	135.566	—	135.566	—	—

Table shows averages for baseline. The last column is the coefficient of a simple regression of treatment status on the variable, with robust standard errors. The groups are perfectly matched for gender, occupation, and state. Stars indicate whether this difference is significant. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

3 Empirical strategy

We are interested in exploring how workers in different occupational groups respond to a sudden shock in their careers. In doing so, we follow extensive literature and employ an event-study approach (Blien et al., 2021; Couch and Placzek, 2010; Jacobson et al., 1993; Raposo et al., 2019). Mass layoffs are taken as external shocks to estimate the effect of an involuntary job loss on earnings and employment prospects. In essence, we aim to compare

the wage and employment changes of treated individuals over the medium-run with the wage changes that would have occurred if they had not lost their jobs. Given that we aren't able to observe the latter, we build a control group. In doing so, a robust methodology is the use of matching techniques in combination with difference-in-differences (DiD) methods (see Blien et al., 2021; Cunningham, 2021; Heckman et al., 1997). Following the matching procedure described in the previous section, we follow Jacobson et al. (1993) and estimate:

$$y_{it} = \alpha_0 + \sum_{k=-3,k\neq-2}^{5} [\nu_t^k + \nu_t^k T_i \beta_k] + \lambda_i + \theta_t + \delta_s + \sigma_j + \epsilon_{ijst} \tag{1}$$

where y_{it} is the outcome of interest (relative monthly salary or employment). Relative wages are measured compared to worker's compensation in $t-2$, while employment is a dummy equal to one is the worker has any positive labor earnings in a given year. Wages are taken as zero whenever the individuals are unemployed. T_i is a treatment indicator that is equal to one if the worker faced a layoff and zero otherwise, and ν_t represents time-to-event dummies, from 3 years before the event to five years after it (t-2 is the baseline). The coefficients β_k are our outcome of interest and measure the differences in relative earnings or relative employment for displaced and non-displaced workers from three years before the shock to five years after. λ_i and θ_t represent individual and time fixed effects and capture permanent unobserved individual characteristics and general patterns in the economy, respectively. In contrast, σ_j and δ_s represent common region and sector effects. To estimate the difference between routine and non-routine occupations, we follow Blien et al. (2021) and modify Equation 1 such that:

$$y_{it} = \alpha_0 + \sum_{k=-3,k\neq-2}^{5} [\nu_t^k + \nu_t^k T_i \beta_k + \nu_t^k RTI_i \alpha_k] + \sum_{k=-3,k\neq-2}^{5} \nu_t^k T_i RTI_i \rho_k + \lambda_i + \theta_t + \delta_s + \sigma_j + \epsilon_{ijst} \tag{2}$$

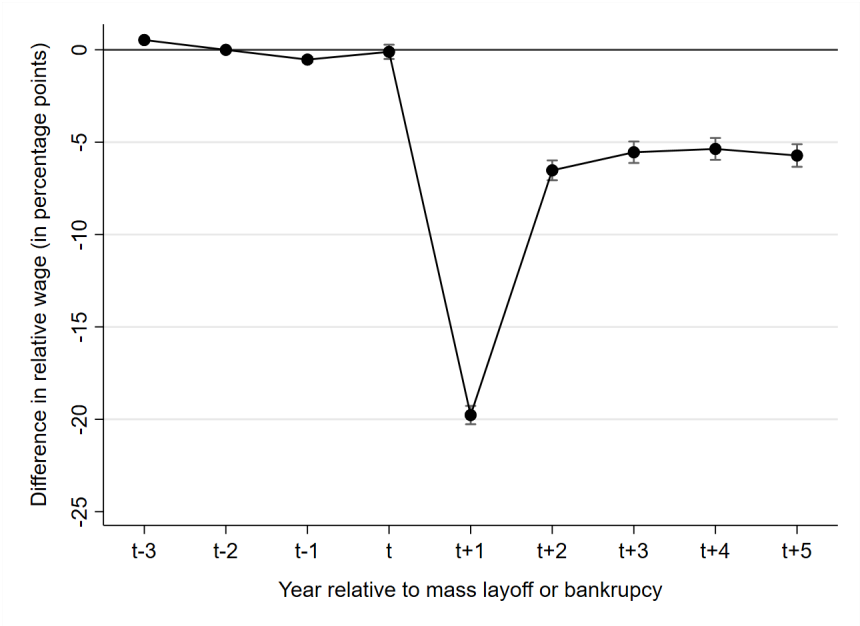
where RTI_i is the routine intensity index described in Table 1. In addition to worker fixed effects, time-to-event dummies, and regular year, region, and sector dummies, Equation 2

also includes interactions between time-to-event dummies and routine intensity ($\alpha_k \nu_t^k RTI_i$) and the triple interaction between routine intensity, treatment, and time to event dummies ($\sum_{k=-3}^{5} \nu_t^k T_i RTI_i \rho_k$). The interaction between time-to-event dummies and routine intensity captures common trends in the occupational groups irrespective of treatment, while the triple interaction term measures the additional effect in a specific year due to an increase in the routine intensity index. The latter is our main outcome of interest.

4 The adverse effects of job displacement

We start by first exploring the impact of job displacement on wages and employment in Brazil. Figure 2 plots the coefficients from Equation 1 and shows as expected that displaced individuals face a substantial decline in relative wages in $t + 1$ compared to the control group, which is only partially recovered in the following years. For instance, in t+5, treated individuals earn over 5% less than the control group. The identifying restriction rests on whether displaced and non-displaced workers have parallel trends in the outcome variables before the event. In the years before the displacement, the coefficients were not statistically different from zero, which implies that the earnings profiles of workers were the same up to the shock. However, following the shock, treated workers earn substantially less (about 20%) than two years before the event. Our results are larger than those in Saltiel (2018) but much smaller than those from Menezes-Filho (2004), who found salary losses of up to 30%. The differences with our results are likely related to differences in our sample. For instance, Saltiel (2018) focuses on displaced workers that find a job in the year of displacement, thus resulting in estimates that are biased towards smaller negative effect sizes. On the other hand, in addition to focusing exclusively on the state of São Paulo, Menezes-Filho (2004) does not perform a matching between control and treated workers, thus likely resulting in larger negative results.

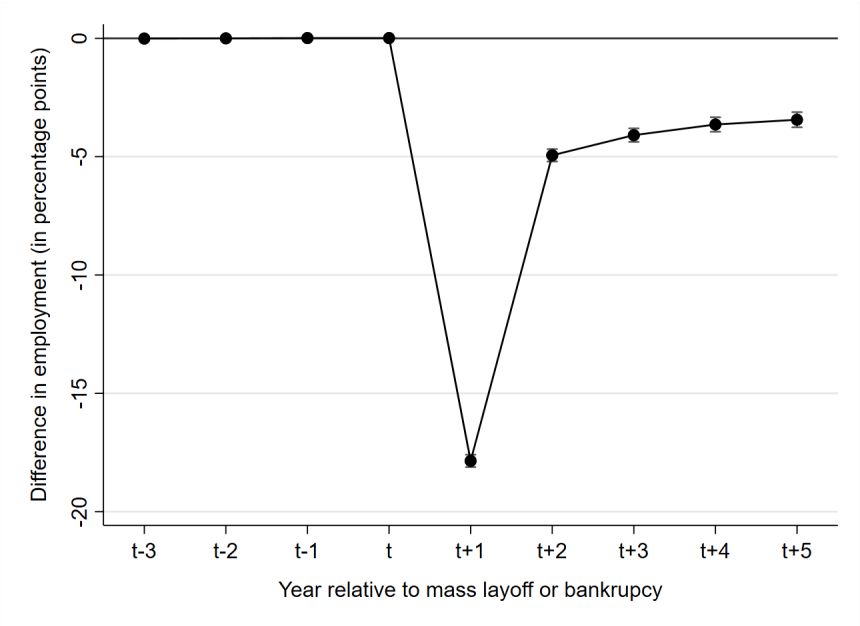
Figure 2: Effect of displacement on relative wages



The figure shows the estimates of time-to-event dummies interacted with a displacement indicator from a regression including individual, region, sector, time-to-event dummies, and year fixed effects. The dependent variables is relative wages. Relative wages are measured dividing worker's monthly average wage by the worker's average wage in year $t-2$. Year $t-2$ is the base year. Vertical bars show estimated 95% confidence interval based on standard errors clustered at individual level.

Figure 3 presents the effect on the other outcome of interest, workers' employment. In years preceding the shock, given that workers were employed full-time, the coefficients are equal to zero. However, following the displacement, treated workers are 18% less likely to be in formal jobs than the control group. In the following years, the impact on employment declines to 5%, with the impact lasting over the medium-run. For instance, in year t+5, displaced individuals are 3.4% less likely to be in formal employment than the control group (Table A1 in the Appendix presents the coefficients for each year).

Figure 3: Effect of displacement on employment



The figure shows the estimates of time-to-event dummies interacted with a displacement indicator from a regression including individual, region, sector, time-to-event dummies, and year fixed effects. The dependent variables is employment. Employment is a dummy equal to one is the worker has any positive labor earnings in a given year. Year $t-2$ is the base year. Vertical bars show estimated 95% confidence interval based on standard errors clustered at individual level.

We further explore the heterogeneity of our results and group workers into different categories to examine some of the drivers of the adverse effects of displacement. Table 3 shows the baseline estimates of the averages of the estimates over the 6 years from the shock (from t to $t+5$) of time-to-event dummies interacted with a displacement indicator from a regression including individual, region, sector, time-to-event dummies, and year fixed effects.

Table 3: Effect of displacement on relative wages and employment by group

	Relative wages		**Relative employment**		
	Mean effect	*Stand. Errors*	*Mean effect*	*Stand. Errors*	*Observations*
Age					
40 years or younger	-0.0726***	(0.00232)	-0.0524***	(0.00114)	1.734.309
41 years or older	-0.0688***	(0.00314)	-0.0662***	(0.00184)	702.449
Tenure					
72 months or less	-0.0646***	(0.00242)	-0.0489***	(0.00124)	1.547.145
73 months or more	-0.0845***	(0.00300)	-0.0694***	(0.00155)	889.612
Education					
Without high-school	-0.0536***	(0.00269)	-0.0557***	(0.00149)	1.027.583
High-school	-0.0819***	(0.00276)	-0.0550***	(0.00138)	1.201.266
College graduate	-0.101***	(0.00757)	-0.0689***	(0.00339)	207.909
Gender					
Female	-0.0886***	(0.00347)	-0.0756***	(0.00190)	779.831
Male	-0.0635***	(0.00224)	-0.0473***	(0.00110)	1.656.927
Firm size					
100 or less employees	-0.104***	(0.00368)	-0.0799***	(0.00185)	735.912
101 or more employees	-0.0579***	(0.00219)	-0.0476***	(0.00114)	1.700.846

The table shows averages of the estimates over the 6 years from the shock (from t to $t+5$) of time-to-event dummies interacted with a displacement indicator from a regression including individual, region, sector, time-to-event dummies, and year fixed effects. In other words, the table shows the "average over years" obtained from a single dummy variable for the entire period t:t+5. The dependent variables are relative wages and employment. Relative wages is measured dividing worker's monthly average wage by the worker's average wage in year $t-2$. Employment is a dummy equal to one is the worker has any positive labor earnings in a given year. Year $t-2$ is the base year. Standard errors clustered at individual level are reported in parenthesis. ***, ** and * respectively indicate 0.01, 0.05 and 0.1 levels of significance.

Several interesting facts emerge. First, in terms of employment, and consistent with the literature (Deelen et al., 2018), the adverse effects are more significant for older workers. 41 years or older workers face a decline in employment about 1 percentage points larger than younger individuals. In contrast, older workers are less affected in terms of relative wages. In addition, similar to Saltiel (2018), the impact is more significant for long-tenured workers, reflecting the importance of breaking employer-employee matching and the destruction of firm-specific human capital for explaining sustained wage losses. Workers with over 72 months of experience in the same firm see their wages declining on average 8% relative to two years before the displacement, while short-tenured individuals see a decline of 6%. Long tenured workers are also more impacted by a decrease in relative employment (6.9%) than short-tenure workers (4.8%). We also find that male workers are less impacted than female individuals in terms of relative wages and employment. The results are different to those

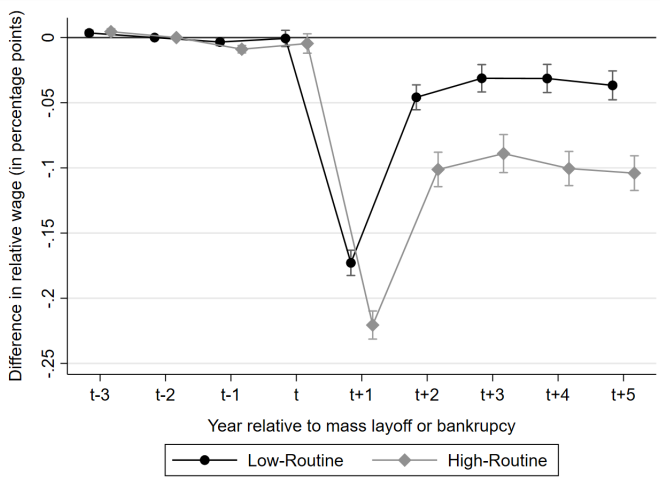
observed in Carneiro and Portugal (2006), who use Portuguese matched employer-employee database and find that the effects of displacement are larger for men (12%) than women (9%). In addition, we find that high-educated workers are more significantly affected both in terms of wages and employment. Furthermore, workers in smaller companies see a more substantial decline in wages and employment than those in larger companies.

5 Routine intensity and the cost of displacement

5.1 The role of tasks

Mass layoffs are a natural experiment to explore the role of routine intensity in the impact on workers, given that they represent an exogenous and often unexpected shock to workers. If wages solely reflect workers' observable characteristics, pre- and post- displacement wages should show minor variation. However, some factors external to the worker can affect the labor outcomes of the displaced. Critical among these factors are those that affect routine intensity of those tasks. A first element that suggests that the type of tasks carried out by the worker matters is technology. Technological progress does not equally affect all occupations. For example, a well known fact is that automation diminishes the demand for routine tasks (Autor and Dorn, 2013), so that workers in routine-intensive occupations suddenly find themselves in a less favorable market, making it a challenge to recover from losing their jobs. Arnoud (2018) shows that even under low technology adoption, the threat of automation can lower wage growth of occupations more susceptible to automation. Second, structural transformation and the decreasing share of manufacturing in the economy can also reduce the demand for routine intensive occupations and worsen the outcomes of displaced workers in those sectors (Bárány and Siegel, 2018).

Figure 4: Effect of displacement on relative wages by occupational group

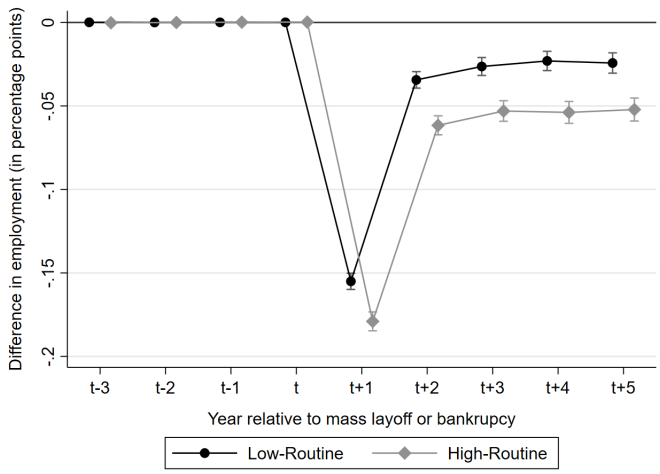


The figure shows the estimates of time-to-event dummies interacted with a displacement indicator from a regression including individual, region, sector, time-to-event dummies, and year fixed effects. The dependent variables is relative wages. Relative wages is measured dividing worker's monthly average wage by the worker's average wage in year $t-2$. Year $t-2$ is the base year. Low-routine are workers in the first quartile of the routine-intensity index, while high-routine indicates workers in the fourth quartile. Vertical bars show estimated 95% confidence interval based on standard errors clustered at individual level.

Figure 4 provides a first glance at the impact of job displacement on workers' wages for different occupational groups. Using the routine-intensity index described in Table 1, we group workers into low-routine occupations (first quartile) and high-routine occupations (fourth quartile). The figure compares both groups and shows that workers in high-routine occupations are substantially more harmed than those at the bottom of the routine distribution. The decline in wages in $t+1$ is over 5% larger for workers in the fourth quartile, with the effect persisting over the medium run.

Table A2 shows the results of a similar exercise than in Table 3, and reinforces the fact that workers in high-routine occupations are more impacted in terms of wages. In addition, Figure 5 shows that workers in the fourth quartile are 2% more likely to face unemployment in the years following the shock.

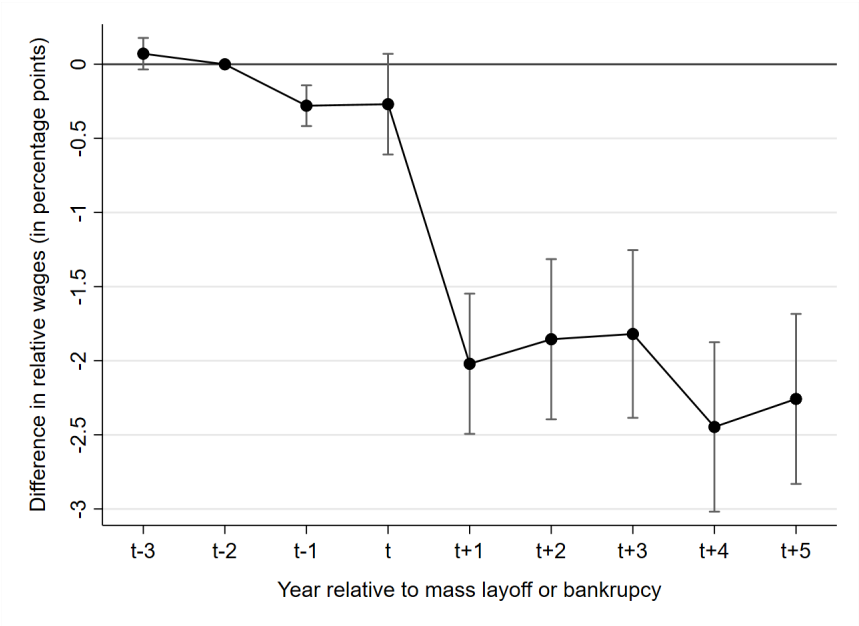
Figure 5: Effect of displacement on employment by occupational group



The figure shows the estimates of time-to-event dummies interacted with a displacement indicator from a regression including individual, region, sector, time-to-event dummies, and year fixed effects. The dependent variables is employment. Employment is a dummy equal to one is the worker has any positive labor earnings in a given year. Year $t-2$ is the base year. Low-routine are workers in the first quartile of the routine-intensity index, while high-routine indicates workers in the fourth quartile. Vertical bars show estimated 95% confidence interval based on standard errors clustered at individual level.

These initial results, however, do not account for some critical differences between occupational groups; especially the fact that trends in wages might differ between occupational groups. A more formal estimate is presented in Figure 6, which offers the estimates from Equation 2 and presents the coefficient of the triple interaction term (ρ_k) taking relative wages as the dependent variable. Table A5 in the Appendix show the coefficients for both wages and employment. The interpretation of these estimates is by how many percentage points the earnings loss in a specific year is magnified due to an increase in 1 point in the routine intensity index, which in turn varies from -1.52 to 2.24.

Figure 6: Routine task intensity and the effect of displacement on relative wages

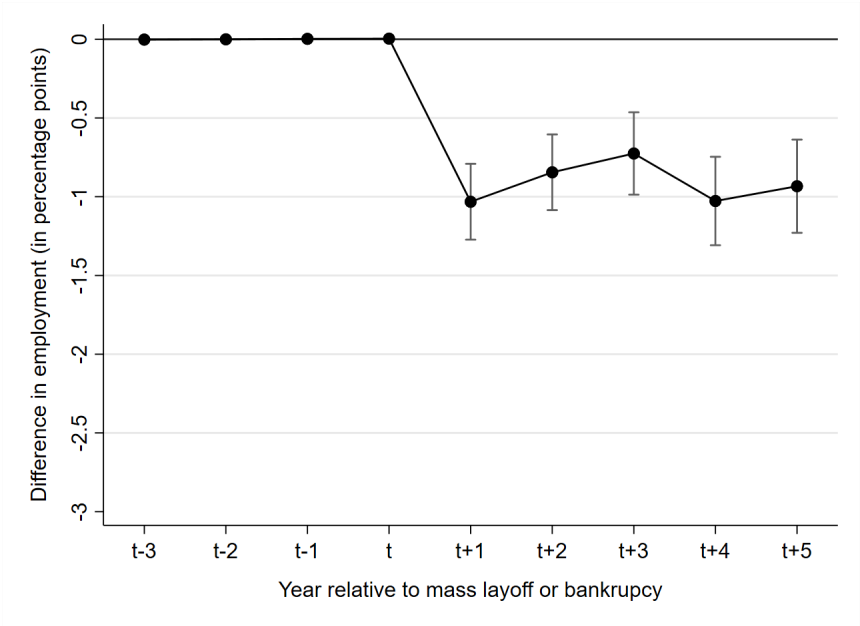


The figure shows the estimates of the triple interactions between time-to-event dummies interacted with a displacement indicator and a routine intensity measure from a regression including individual, region, sector, time-to-event dummies, time-to-event dummies interacted with the routine intensity measure, and year fixed effects. The dependent variables is relative wages. Relative wages is measured dividing worker's monthly average wage by the worker's average wage in year $t-2$. Year $t-2$ is therefore the base year. Vertical bars show estimated 95% confidence intervals based on standard errors clustered at individual level.

The results suggest that an increase in 1 point in the RTI results in a further decline of about 2% on relative wages across the years and up to five years following the shock. For instance, a worker previously employed in metal and machinery (RTI equals 0.46) would face a decline 2% lower than a worker once hired as precision, handicraft, and craft printing (RTI equals 1.59). In addition, Figure 7 shows that workers in routine-intensive occupations are also more likely to face more extended periods of unemployment – a 1 point increase in the RTI increases the chance of unemployment by 1%. Our findings are similar to those in Blien et al. (2021) and Goos et al. (2021), who also find a negative impact of being previously employed in routine-intensive occupations. In addition, the results are somewhat consistent with Firpo et al. (2021), who find some evidence of earnings polarization in Brazil.[4]

[4]Regarding the more significant adverse effect of displacement for workers in high routine occupations, Table A3 suggests that these workers are less likely to be part of a mass layoff (compared to a firm closure). Workers experiencing a mass layoff are significantly less routine intensive on average than workers experiencing a firm closure (RTIs of 0.17 vs 0.31 respectively, p-value $< 10\%$).

Figure 7: Routine task intensity and the effect of displacement on employment



The figure shows the estimates of the triple interactions between time-to-event dummies interacted with a displacement indicator and a routine intensity measure from a regression including individual, region, sector, time-to-event dummies, time-to-event dummies interacted with the routine intensity measure, and year fixed effects. The dependent variables is employment. Employment is a dummy equal to one is the worker has any positive labor earnings in a given year. Year $t-2$ is therefore the base year. Vertical bars show estimated 95% confidence intervals based on standard errors clustered at individual level.

Keeping our focus on job displacement and routine intensity, we investigate the robustness of our findings according to heterogeneity in individuals' characteristics.[5] Table 4 examines the heterogeneity of these findings, as in Table 3, while estimating Equation 2. Some interesting findings emerge in the analysis of relative wages. First, as in the previous results, the effect of routine-intensity is larger for long-tenured individuals. Second, we observe that the impact is more significant for male and less-educated individuals. Lastly, the impact is larger for workers previously employed in larger establishments. As for employment, we observe similar results. Older and long-tenure individuals face more extended periods of unemployment. In addition, female and college graduate workers don't show statistically significant results. In the following section, we try to account for these significant impacts,

[5]We cannot rule out that our estimates for RTI and displacement outcomes may not correspond to causal estimates of RTI on displacement outcomes, because of potential correlations between RTI and workers' characteristics (such as gender, education, or other variables that remain unobserved). While a detailed analysis of workers' characteristics is beyond the scope of the current paper, further work on different samples would be welcome.

considering differences across sectors, the role of job switchers, and firm heterogeneity.

Table 4: Effect of routine intensity on relative wages and employment by group

	Relative wages		**Relative employment**		
	Mean effect	*Stand. Errors*	*Mean effect*	*Stand. Errors*	*Observations*
Age					
40 years or younger	-0.0141***	(0.00223)	-0.00651***	(0.00105)	1.687.041
41 years or older	-0.0253***	(0.00307)	-0.0128***	(0.00173)	677.402
Tenure					
72 months or less	-0.0126***	(0.00236)	-0.00521***	(0.00115)	1.504.215
73 months or more	-0.0243***	(0.00289)	-0.0113***	(0.00142)	860.227
Education					
Without high-school	-0.0284***	(0.00286)	-0.0153***	(0.00151)	976.112
High-school	-0.0119***	(0.00257)	-0.00586***	(0.00123)	1.193.220
College graduate	-0.00236	(0.00658)	0.00187	(0.00293)	195.111
Gender					
Female	-0.00973***	(0.00349)	0.00186	(0.00175)	758.996
Male	-0.0187***	(0.00217)	-0.00930***	(0.00104)	1.605.447
Firm size					
100 or less employees	-0.00307	(0.00356)	0.000296	(0.00168)	706.671
101 or more employees	-0.0212***	(0.00213)	-0.00941***	(0.00106)	1.657.772

The table shows averages of the estimates over the 6 years from the shock (from t to $t+5$) of the triple interactions between time-to-event dummies interacted with a displacement indicator and a routine intensity measure from a regression including individual, region, sector, time-to-event dummies, time-to-event dummies interacted with the routine intensity measure, and year fixed effects. In other words, the table shows the "average over years" obtained from a single dummy variable for the entire period t:t+5. The dependent variables are relative wages and employment. Relative wages is measured dividing workers monthly average wage by average wage in year $t-2$. Employment is a dummy equal to one is the worker has any positive labor earnings in a given year. Standard errors clustered at individual level are reported in parenthesis. ***, ** and * respectively indicate 0.01, 0.05 and 0.1 levels of significance.

Our main finding suggests that workers in routine-intensive occupations face a more considerable decline in wages and employment following a mass layoff. In other words there is evidence of non-routinization affecting workers outcomes in Brazil, given that the falling demand for routine workers has impacted their ability to find similar, good-paying jobs. As a result, a critical question is to understand what are the main the mechanisms that could explain these effects on workers.

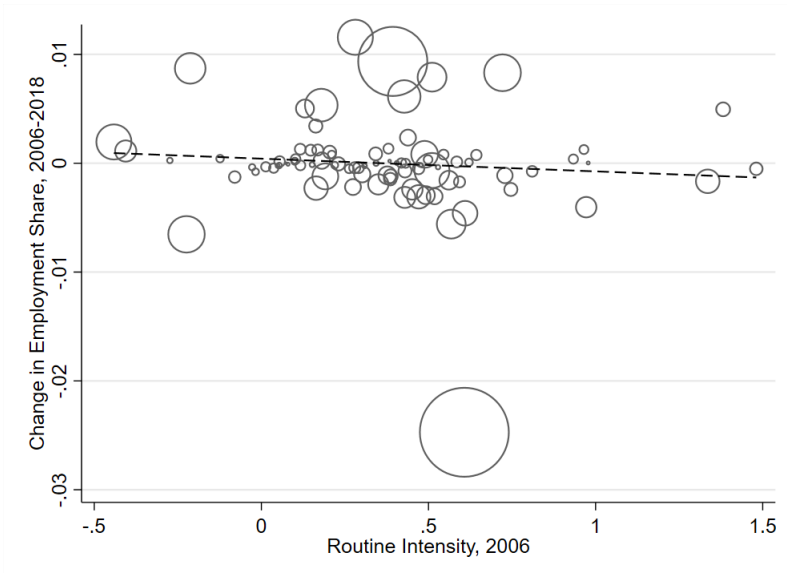
5.2 The role of decreasing demand

In exploring the possible mechanisms, we first look at differences in the demand for routine occupations across sectors and test whether workers initially employed in industries with

falling demand for routine tasks are more considerably affected. Second, we test for the importance of job switchers in explaining our results. For example, following a displacement and given the lower demand for these occupations, workers may move to occupationally distant jobs, which is usually associated with lower re-employment wages (Huckfeldt, 2018; Lysho, 2020). Therefore, we examine first whether workers in routine occupations are more likely to switch fields, and then we test for different impacts among switchers and non-switchers. Lastly, differences in firm characteristics can help shed some light on our results. In particular, there are significant differences in firms' wage premiums in Brazil (Alvarez et al., 2018). In this context, we examine whether workers in routine occupations are more likely to move to low-paying firms upon re-employment. Given the decline in the demand for such occupations, displaced individuals could face more difficulties finding a better-paying firm, thus, ending with a lower wage.

Figure 1 shows a constant decline in routine intensity in Brazil from 2006 to 2018. Yet, the aggregate measure hides significant heterogeneity across sectors. The decrease in the demand for routine occupations combines within-industry and between-industry changes. On the one hand, as firms adopt more sophisticated and automated technologies, a given industry will use less routine employment to produce similar output levels. On the other hand, routine intensity differs across sectors, such that sectoral employment shifts also explain aggregate occupational share changes (Goos et al., 2014).

Figure 8: Routine Intensity and Change in Industries' Employment Share



Circles represent 87 sectors, weighted by total employment in 2006. The x-axis is the RTI index, calculated as the weighted occupational index. The y-axis is the change in the share of employment in each sector from 2006 to 2018, measured in percentage points. The coefficient in the linear regression is -0.00117, with standard error equal to 0.0012.

As a first exercise, we test for the association between initial routine intensity across sectors and the change in employment share from 2006 to 2018. Figure 8 shows a negative correlation, albeit weak, between RTI and employment change across industries in Brazil, hence suggesting that most of the changes in the index might have occurred within sectors. To have a better grasp of these dynamics, we decompose the difference from 2006 to 2018 in the RTI index into changes within and between industry groups:

$$\Delta RTI = \sum_i \Delta RTI_i S_{i0} + \sum_i RTI_{i0} \Delta S_i + \sum_i \Delta RTI_i \Delta S_i \tag{3}$$

where i indexes industries. RTI_i accounts for the routine-intensity (measured as the occupational weighted index) of industry i and ΔRTI_i accounts for the change in RTI of unit i. S_i is the share of industry i in total employment, and ΔS_i is the change in the share in total employment of industry i over the period. The first term in the RHS is the contribution of RTI growth in each industry (*within industry*), assuming that employment shares remain unchanged. The second term in the RHS is related to changes in employment shares

(*between industry*), while the RTI index in each sector is kept constant. Finally, the third term is a *dynamic* term, giving the contribution to the total RTI index due to a rise in the employment share in sectors whose RTI has increased in the period.

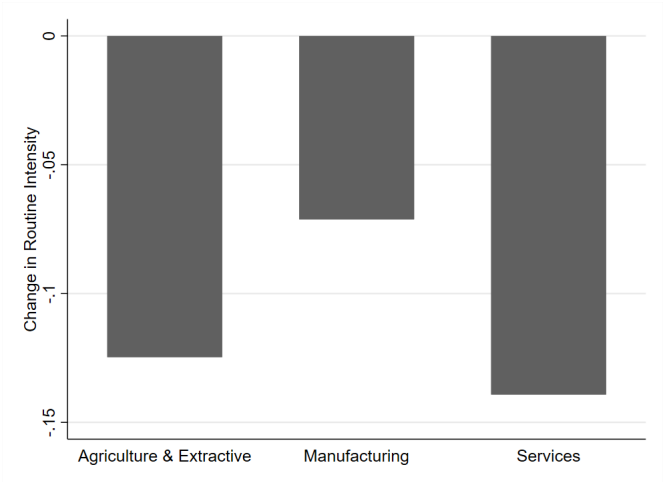
Table 5: RTI decomposition, 2006-2018

Mean		
RTI 2006	RTI 2018	Total Change
0.402	0.283	-0.12
Decomposition (Raw)		
Within	Between	Dynamic
-0.112	-0.012	0.005
Decomposition (Percentage)		
Within	Between	Dynamic
0.94	0.10	-0.04

All proportions and means are weighted by occupational employment in 2006 or 2018. Δ is the change in the average proportion or mean from 2006 to 2018.

Table 5 presents the results of the shift-share decomposition. From 2006 to 2018, the RTI index in Brazil dropped 0.12 points (30%), explained mainly by changes within sectors. Specifically, 94% of the decline is explained by within-sector variations, while between sector changes explain only 10%. Figure 9 presents the change in routine intensity across sector over the period. (Table A6 in the Appendix shows the within-sector change in RTI for the 87 sectors over the period, ranked according to the size of the decline). Although most research relates the decline in routine tasks to automation in manufacturing, the services industry presents a more significant decrease in routine intensity in Brazil. In particular, the decline in routine intensity in services was twice as large as that for manufacturing. Hence, we document a significant decrease in routine occupations not related to reallocation of workers but to within sector changes, and that go beyond manufacturing.

Figure 9: Change in Sectors' Routine Intensity



The y-axis is the mean change in RTI for each sector from 2006 to 2018.

Our next step lies in using these differences across sectors. First, we divide our sample into workers initially employed in manufacturing and non-manufacturing and re-estimate Equation 2. In addition, we look at within-industry changes in the RTI index and split our sample into individuals initially employed in sectors above the median or below or equal the median. Table 6 presents the results of both exercises, suggesting that workers previously employed in manufacturing face a larger decline on wages and more extended periods of unemployment. Furthermore, when focusing on the decline in RTI across industries, the impact is more considerable for sectors with a more significant decline in the demand for routine tasks. Therefore, demand seems to be playing a sizable role in explaining differences across occupational groups in Brazil.

Table 6: Effect of displacement on wages by sector group

	Relative wages		Relative employment		
	Mean effect	*Standard Errors*	*Mean effect*	*Standard Errors*	*Observations*
Sector					
Manufacturing	-0.0204***	(0.00361)	-0.00954***	(0.00176)	864.288
Non-Manufacturing	-0.0140***	(0.00215)	-0.00609***	(0.00105)	1.500.156
Sector					
Below or equal the median	-0.0127***	(0.00359)	-0.00260	(0.00167)	677.844
Above the median	-0.0196***	(0.00211)	-0.00995***	(0.00106)	1.686.600

The table shows the baseline estimates of averages of the triple interactions between time-to-event dummies interacted with a displacement indicator and a routine intensity measure from a regression including individual, region, sector, time-to-event dummies, time-to-event dummies interacted with the routine intensity measure, and year fixed effects. The dependent variables are relative wages and employment. Relative wages is measured dividing workers monthly average wage by average wage in year $t-2$. Employment is a dummy equal to one is the worker has any positive labor earnings in a given year. Year $t-2$ is the base year. Columns (1) and (2) split the 87 sectors between non-manufacturing and manufacturing. Columns (3) and (4) split the sample into those with a decline in the RTI index below the median and above the median. The median is equal to -.055. Standard errors clustered at the individual level are reported in parenthesis. ***, ** and * respectively indicate 0.01, 0.05 and 0.1 levels of significance.

5.3 Job switchers

Within a more competitive labor market, with few opportunities, workers in routine occupations could be more inclined (or forced) to change fields in search for better, high-paying jobs. In this section, we estimate whether workers in routine-intensive occupations are more likely to move to different professions following a layoff and the impacts of these transitions. In doing so, we create a dummy equal to 1 if individuals switch occupations (2-digits) and zero otherwise. In our sample, switching to a different occupation is observed for 49.743 workers (about 20% of individuals) (see Table A4 for a descriptive analysis of switchers and non-switchers). Columns (1)-(2) in Table 7 show baseline estimates that include a set of Mincerian workers' characteristics and year, sector, and region effects. The columns differ in methodology, with column (1) using a ordinary least squares model (OLS), while column (2) employs a probit model. In addition, columns (3)-(4) show similar regressions using a different definition of job switchers, now including only individuals that change broader occupations (1-digit).

Table 7: Routine-intensity and the probability of switching occupations

	Dependent variable: dummy indicator of switching occupations			
	(1) OLS	(2) Probit	(3) OLS	(4) Probit
RTI	0.0135***	0.0684***	0.0116***	0.0626***
	(0.000976)	(0.00412)	(0.000938)	(0.00426)
Treated	0.0872***	0.342***	0.0723***	0.309***
	(0.00149)	(0.00607)	(0.00142)	(0.00626)
Treated × RTI	0.0158***	0.0249***	0.0130***	0.0216***
	(0.00136)	(0.00522)	(0.00130)	(0.00537)
Female	-0.0200***	-0.0767***	-0.0231***	-0.0948***
	(0.00199)	(0.00738)	(0.00190)	(0.00764)
Worker's age	0.000166	-0.0315***	-0.000406	-0.0352***
	(0.00114)	(0.00414)	(0.00108)	(0.00421)
Squared age	-0.0000685***	0.000150***	-0.0000534***	0.000208***
	(0.0000152)	(0.0000563)	(0.0000143)	(0.0000572)
Tenure	-0.000337***	-0.00152***	-0.000287***	-0.00140***
	(0.0000174)	(0.0000799)	(0.0000166)	(0.0000826)
Primary school graduate	0.0169***	0.0192	0.0150***	0.0206
	(0.00540)	(0.0234)	(0.00495)	(0.0247)
Middle school graduate	0.0293***	0.0743***	0.0275***	0.0806***
	(0.00539)	(0.0231)	(0.00495)	(0.0243)
High-school graduate	0.0281***	0.0718***	0.0293***	0.0893***
	(0.00536)	(0.0229)	(0.00494)	(0.0242)
College degree	0.0515***	0.165***	0.0547***	0.195***
	(0.00611)	(0.0252)	(0.00569)	(0.0264)
Log(firm size)	-0.00372***	-0.0208***	-0.00261***	-0.0173***
	(0.000670)	(0.00258)	(0.000638)	(0.00268)
Year	Yes	Yes	Yes	Yes
Region	Yes	Yes	Yes	Yes
Sector	Yes	Yes	Yes	Yes
Observations	262716	262714	262716	262711

The table shows the baseline estimates of switching occupations and a routine intensity measure from a regression including individual, region, sector, and year. In columns (1) and (2), the dependent variable is a dummy variable equals to one if individuals switch occupations (2-digits) and zero otherwise. In columns (3) and (4) we use a broader definition of occupation and define workers' occupations at 1-digit level. Therefore, the dependent variable is equal to 1 if workers transition across occupations at 1-digit and zero otherwise. Robust standard errors are reported in parenthesis. ***, ** and * respectively indicate 0.01, 0.05 and 0.1 levels of significance.

The main finding is that the routine-intensity index correlates significantly with the probability of moving to different occupations, even if not in the treatment group. The

second line in Table 7 shows that treated workers (those part of a mass layoff) are also more likely to switch occupations, consistent with other findings in the literature (Nedelkoska et al., 2015). We also find that treated individuals previously employed in routine occupations are more likely to transition to different professions. In addition, we observe that male and more educated workers are more likely to switch jobs, whereas long-tenured individuals are less likely to follow this path. Overall, the results suggest that the falling demand for routine tasks not only affects workers' employment outcomes but also increases the likelihood to change professions.

We further test whether displacement affects job switchers differently compared to non-switchers. In particular, we separate our sample between job switchers and those workers that remained in the same occupation (2-digits) and re-estimate Equation 2. Column (1) in Table 8 presents the results for the group of workers that switch occupations and column (2) for the workers that have remained in the same occupational group. Interestingly, workers initially in routine-intensive occupations and moving to different occupations are significantly less affected than workers who do not switch occupations. This aligns nicely with economic intuition. Falling demand for routine tasks requires the reallocation of workers from declining occupations to other more promising – workers who comply with such inter-occupational selection dynamics should be rewarded compared to workers who "stubbornly" linger in their original declining occupation. Similarly, workers switching to other occupations presumably select from amid a broader opportunity set than workers searching only within their current occupation. Hence switching workers would be associated with a better-matching labor market opportunity if their search space is wider.

Table 8: Effect of displacement on wages for switchers and non-switchers

	Dependent variable: relative wages	
	(1) Switchers	(2) Non-switchers
Mean effect	-0.0698***	-0.0865***
	(0.00534)	(0.00208)
RTI	-0.00769	-0.0242***
	(0.00512)	(0.00195)
Individual	Yes	Yes
Year	Yes	Yes
Region	Yes	Yes
Observations	446886	1917558
R-squared	0.374	0.374

The table shows averages of the estimates over the 5 years from the shock (from t to $t+4$) of the triple interactions between time-to-event dummies interacted with a displacement indicator and a routine intensity measure from a regression including individual, region, sector, time-to-event dummies, time-to-event dummies interacted with the routine intensity measure, and year fixed effects. The dependent variable is relative wages. Relative wages is measured dividing workers monthly average wage by average wage in year $t-2$. Year $t-2$ is the base year. Job switchers are defined as workers that change occupations between the year before the shock and the first year of re-employment. Occupations are defined at the 2-digit level. Column (1) restrict the sample to switchers, while column (2) focus on non-switchers. Standard errors clustered at the individual level are reported in parenthesis. ***, ** and * respectively indicate 0.01, 0.05 and 0.1 levels of significance.

5.4 Firms fixed effects

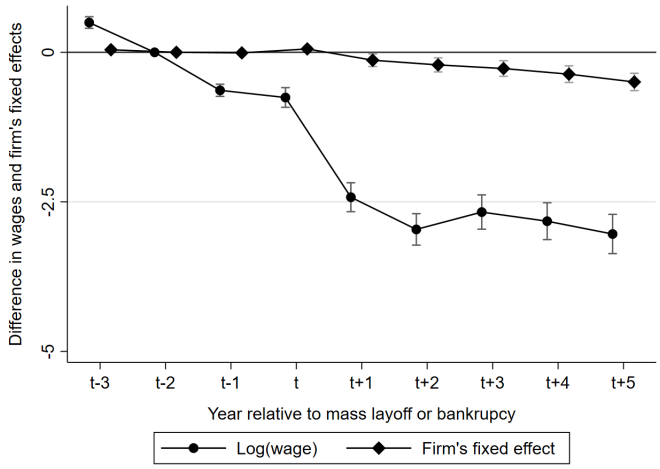
A third and related mechanism to explain worse employment outcomes for routine occupations is that workers in high routine intensive occupations have to move to low-paying and worse companies to find a job in the same field. For instance, less productive firms tend to have lower adoption of more sophisticated technologies, thus continuing to demand labor to perform routine tasks and being the main option for dismissed high-routine workers.

To test this hypothesis, we estimate whether workers in routine-intensive occupations move to low-paying companies more frequently. First, we estimate firms' paying heterogeneity and decompose earnings using an AKM decomposition. Specifically, to calculate firms' fixed effects, we regress the log of monthly wages on a set of individual, firm, and year fixed effects. To ease the computational burden, we estimate this specification for two different periods - 2007 to 2012 and 2013 to 2018, and limit the sample to the largest connected set

within each of these samples.[6]

With firms fixed effects in hand, we estimate Equation 1 using the fixed effects as the outcome variable and compare with the impacts on workers' logarithm of monthly wages. Figure 10 shows the results of this exercise, indicating that the loss of employer-specific wage premium responds to about 13% of the adverse effect on wages. Our results are closer in magnitude to those in Lachowska et al. (2020), who finds that employer-specific premiums explain 17% of wage losses in the state of Washington, but significantly smaller than those observed in Germany (Fackler et al., 2021). The small effect on firm wage premium losses is likely related to a weakening pass-through from firm characteristics to wages in Brazil. For instance, Alvarez et al. (2018) shows the decline in firm productivity pay premium explained about 40% of the decrease in earnings inequality in Brazil between 1996 and 2012. As a result, workers are increasingly more likely to move to firms with equal paying premiums.

Figure 10: Job displacement and the loss of employer-specific wage premium



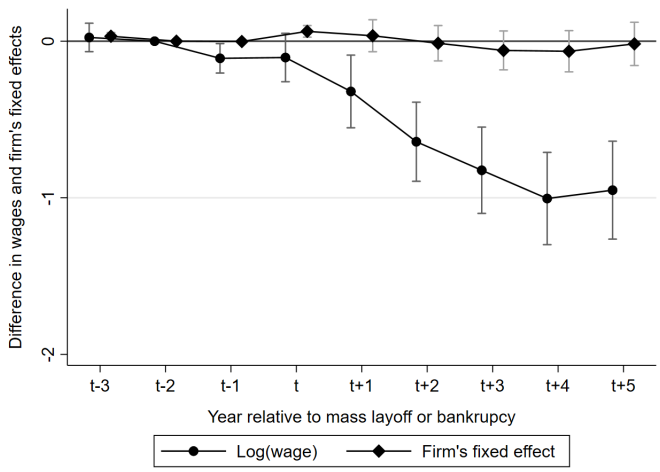
The figure shows the estimates of time-to-event dummies interacted with a displacement indicator from a regression including individual, region, sector, time-to-event dummies, and year fixed effects. The dependent variables are logarithm of monthly wages and firms' fixed effects. Firms' fixed effects are identified using a AKM model. Year $t-2$ is the base year. Low-routine are workers in the first quartile of the routine-intensity index, while high-routine indicates workers in the fourth quartile. Vertical bars show estimated 95% confidence interval based on standard errors clustered at individual level.

Following this analysis, we estimate Equation 2 to test whether the RTI is associated with

[6]We assume that establishments' wage premium is set at the firm level. Therefore, we estimate establishments fixed effects at the company level.

movements to low-paying firms. On the one hand, Figure 11 confirms that workers previously employed in routine-intensive occupations face a more significant decline in wages, even when excluding those workers that are not employed (using the logarithm of wages exclude those workers with missing information on wages). On the other hand, Figure 11 show that the routine-intensity index is not statistically associated with a decline in firm's fixed effects, thus suggesting that workers previously employed in routine-intensive occupations were not more likely to transition to low-paying firms.

Figure 11: Effect of displacement on employment by occupational group



The figure shows the estimates of the triple interactions between time-to-event dummies interacted with a displacement indicator and a routine intensity measure from a regression including individual, region, sector, time-to-event dummies, time-to-event dummies interacted with the routine intensity measure, and year fixed effects. The dependent variables are logarithm of monthly wages and firms' fixed effects. Firms' fixed effects are identified using a AKM model. Year $t-2$ is therefore the base year. Vertical bars show estimated 95% confidence intervals based on standard errors clustered at individual level.

6 Conclusion

Job polarization and the decrease in the demand for routine occupations have been widely documented in the US and European countries. The main culprit of these changes affecting workers unequally is technological changes. Much less is known about the importance of this phenomenon in developing countries where the rate of diffusion and adoption of advanced technologies is much slower. This paper offers a detailed analysis of the employment dynam-

ics associated with routine workers in Brazil, using mass layoffs as a natural experiment to identify employment effects.

Job displacement has a significant impact on workers' careers. Wages are significantly depressed in the short-run and only recover partially in the medium run. Displaced workers are also more likely to face extended periods of unemployment. The results show a large and statistically significant wage loss associated with job displacement. Workers displaced see wage declines of up to 5% even five years after the displacement event. In addition, consistent with most findings in the literature, we find that female, less-educated, long-tenured, and older workers are more significantly affected by displacement.

But while all workers experience significant declines in wages and employment opportunities following a mass layoff event, those in routine intensive occupations fare much worse. While we cannot measure technological progress directly, the results show that job displacement's adverse outcomes are worse in sectors where the demand for routine jobs has decreased over time. Moreover, not only do workers in routine occupations and sectors with larger demand decline experience more wage losses, but they are also more likely to have to switch occupations. However, we do not find evidence of a necessary move towards "worse" firms.

Some policy prescriptions may tentatively be offered. Workers in routine-intensive occupations appear to be especially vulnerable after a mass layoff, presumably related to the difficulty of finding a new job requiring similar skills. Specifically, we find that the effect is only significant for less-skilled individuals. Public policies need to seek to train and qualify displaced workers, assisting the development of new skills to reduce the harmful impacts of displacement.

More research is needed on the heterogeneity of the results. Especially a more nuanced view of these groups and the tasks they perform and the differences between workers that move to different sectors and occupations. In addition, the design of policy interventions requires a deeper understanding of the skills, especially soft skills, that facilitate job transi-

tion. This is critical to understanding the role of skill mismatch and designing appropriate policies for reinserting routine-intensive workers into the labor market. Finally, as the pace of technological change and automation shows no sign of slowing down, policy interventions for training and reskilling displaced workers can only be expected to grow in importance.

Finally, more granular evidence is needed linking directly events of technology upgrading with changes in the skill composition at the level of the firm over a period of time. Rather than inferring technological trends based on the changes in occupation skills within sectors, more granular data is needed to identify better how specific technologies affect the employment outcomes of different types of workers.

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Appendix A Additional estimates

Figure A1: Histogram routine-intensity index

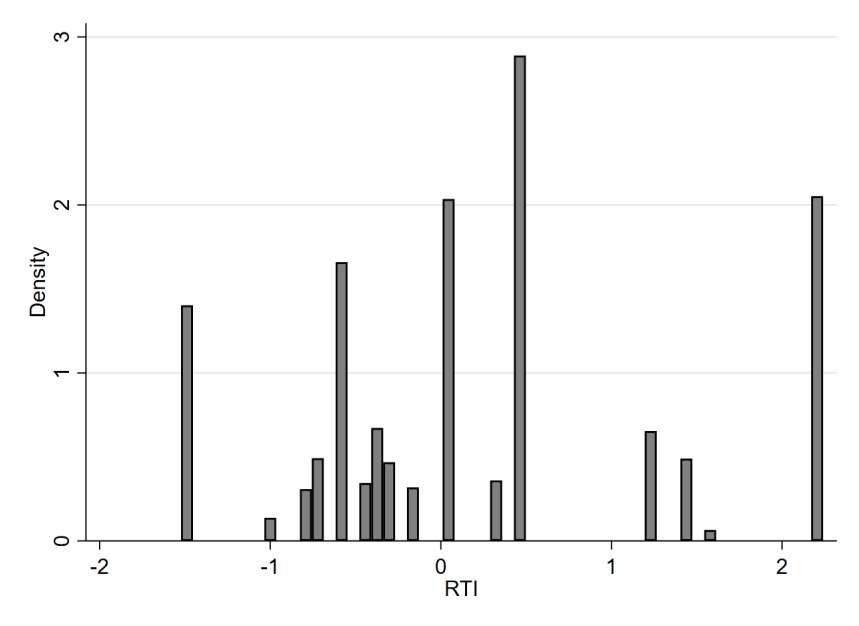

Table A1: Effect of displacement on wages and employment

	Dependent variables	
	(1) Relative wage	(2) Relative employment
Time-to-event (t-3)	0.00533***	-0.0000887***
	(0.000569)	(0.0000261)
Time-to-event (t-2)	—	—
	—	—
Time-to-event (t-1)	-0.00527***	0.000123***
	(0.000776)	(0.0000243)
Time-to-event (t)	-0.00108	0.000111***
	(0.00197)	(0.0000273)
Time-to-event (t+1)	-0.198***	-0.179***
	(0.00253)	(0.00134)
Time-to-event (t+2)	-0.0652***	-0.0494***
	(0.00274)	(0.00134)
Time-to-event (t+3)	-0.0554***	-0.0409***
	(0.00297)	(0.00145)
Time-to-event (t+4)	-0.0536***	-0.0364***
	(0.00302)	(0.00155)
Time-to-event (t+5)	-0.0572***	-0.0344***
	(0.00312)	(0.00163)
Individual	Yes	Yes
Year	Yes	Yes
Region	Yes	Yes
Sector	Yes	Yes
Observations	2.436.759	2.436.759
R-squared	0.379	0.420

The table shows the baseline estimates of the estimates of time-to-event dummies interacted with a displacement indicator from a regression including individual, region, sector, time-to-event dummies, and year fixed effects. The dependent variables are relative wages and employment. Relative wages is measured dividing worker's monthly average wage by the worker's average wage in year $t-2$. Employment is a dummy equal to one is the worker has any positive labor earnings in a given year. Year $t-2$ is the base year. Heteroskedasticity robust standard errors clustered at individual level are reported in parenthesis. ***, ** and * respectively indicate 0.01, 0.05 and 0.1 levels of significance.

Table A2: Effect of displacement on relative wages and employment by occupational group

	Low-Routine	High-Routine
Relative wages	-0.0531***	-0.102***
	(0.00353)	(0.00426)
Relative employment	-0.0438***	-0.0664***
	(0.00184)	(0.00210)
Individual	Yes	Yes
Year	Yes	Yes
Region	Yes	Yes
Sector	Yes	Yes
Clus. individual	Yes	Yes
Observations	659.277	537.543

The table shows the baseline estimates of the estimates of time-to-event dummies interacted with a displacement indicator from a regression including individual, region, sector, time-to-event dummies, and year fixed effects. The dependent variables are relative wages and employment. Relative wages is measured dividing workers monthly average wage by average wage in year $t-2$. Employment is a dummy equal to one is the worker has any positive labor earnings in a given year. Low-routine are workers in the first quartile of the routine-intensity index, while high-routine indicates workers in the fourth quartile. Standard errors clustered at individual level are reported in parenthesis. ***, ** and * respectively indicate 0.01, 0.05 and 0.1 levels of significance.

Table A3: Comparison of workers in establishment's closure and mass layoff

	Closed		Mass layoff		
	Mean	Standard Deviation	Mean	Standard Deviation	Difference
Routine task index	.31	1.09	.17	1.08	-0.143*
Wage	1683	1666.62	1309	1324.80	-370.565***
Wage Growth	.1	0.27	.1	0.25	0.001
Worker's age	35	6.30	35	6.38	0.180
Gender	.34	0.47	.31	0.46	-0.027
Illiterate or primary school	.018	0.13	.033	0.18	0.009**
Primary school graduate	.14	0.34	.19	0.39	0.047***
Middle school graduate	.21	0.41	.26	0.44	0.052***
High-school graduate	.53	0.50	.46	0.50	-0.076***
College degree	.1	0.30	.065	0.25	-0.032**
Tenure	65	43.51	61	42.91	-4.627**
Firm's size	421	505.01	771	1364.19	340.591***
Size (30-49)	.13	0.34	.11	0.32	-0.017
Size (50 - 99)	.18	0.38	.16	0.37	-0.015
Size (100-499)	.4	0.49	.39	0.49	-0.014
Size (500+)	.29	0.45	.34	0.47	0.046
Firm's average wage	1781	1377.09	1337	1025.35	-442.953***
Agriculture and Extractive	.02	0.14	.028	0.17	0.001
Manufacturing	.38	0.49	.34	0.47	-0.038
Services	.6	0.49	.63	0.48	0.037
North	.015	0.12	.024	0.15	0.009**
Northeast	.081	0.27	.15	0.36	0.062***
Southeast	.78	0.42	.64	0.48	-0.132***
South	.11	0.31	.14	0.34	0.031*
Central-West	.021	0.14	.05	0.22	0.030***
Observations	64.433	0.00	71.133	0.00	—

Table shows averages for baseline. The last column is the coefficient of a simple regression of treatment status on the variable, with robust standard errors. Stars indicate whether this difference is significant. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A4: Comparison of switchers and non-switchers

	Non-switcher		Switcher		
Wage	1666	1705.67	1681	1706.56	15.590
Wage Growth	.13	0.42	.14	0.44	0.011*
Worker's age	37	6.37	35	6.01	-1.786***
Gender	.32	0.47	.31	0.46	-0.017
Illiterate or primary school	.02	0.14	.016	0.12	-0.004
Primary school graduate	.16	0.37	.13	0.33	-0.034**
Middle school graduate	.24	0.43	.23	0.42	-0.016
High-school graduate	.5	0.50	.54	0.50	0.040
College degree	.08	0.27	.094	0.29	0.014
Tenure	76	44.34	70	36.66	-6.248***
Firm's size	605	1057.99	591	1122.36	-13.920
Size (30-49)	39	5.79	39	5.76	0.088
Size (50 - 99)	72	14.45	72	14.53	0.246
Size (100-499)	252	112.91	249	111.57	-3.288
Size (500+)	1554	1483.60	1681	1672.40	126.883
Firm's average wage	1686	1318.80	1750	1420.57	64.250
Agriculture and Extractive	.012	0.11	.0091	0.10	-0.003
Manufacturing	.35	0.48	.42	0.49	0.068**
Services	.64	0.48	.57	0.50	-0.065**
North	.02	0.14	.021	0.14	0.002
Northeast	.11	0.32	.11	0.31	-0.005
Southeast	.71	0.46	.71	0.45	0.005
South	.12	0.33	.13	0.33	0.006
Central-West	.038	0.19	.03	0.17	-0.008***
Observations	213.404	—	49.743	—	—

Table shows averages for baseline. The last column is the coefficient of a simple regression of treatment status on the variable, with robust standard errors. Stars indicate whether this difference is significant. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A5: Effect of displacement on wages and employment

	Dependent variable	
	(1) Relative wage	(2) Relative employment
Time-to-event (t-3)	0.000714	-0.0000184
	(0.000542)	(0.0000222)
Time-to-event (t-2)	—	—
	—	—
Time-to-event (t-1)	-0.00279***	0.0000283
	(0.000701)	(0.0000196)
Time-to-event (t)	-0.00269	0.0000416*
	(0.00173)	(0.0000230)
Time-to-event (t+1)	-0.0202***	-0.0103***
	(0.00241)	(0.00123)
Time-to-event (t+2)	-0.0185***	-0.00845***
	(0.00276)	(0.00123)
Time-to-event (t+3)	-0.0182***	-0.00725***
	(0.00289)	(0.00133)
Time-to-event (t+4)	-0.0245***	-0.0103***
	(0.00292)	(0.00143)
Time-to-event (t+5)	-0.0226***	-0.00933***
	(0.00293)	(0.00151)
Individual	Yes	Yes
Year	Yes	Yes
Region	Yes	Yes
Sector	Yes	Yes
Observations	2.364.444	2.364.444

The table shows the baseline estimates of averages of the triple interactions between time-to-event dummies interacted with a displacement indicator and a routine intensity measure from a regression including individual, region, sector, time-to-event dummies, time-to-event dummies interacted with the routine intensity measure, and year fixed effects. The dependent variables are relative wages and employment. Relative wages is measured dividing worker's monthly average wage by the worker's average wage in year $t-2$. Employment is a dummy equal to one is the worker has any positive labor earnings in a given year. Year $t-2$ is the base year. Heteroskedasticity robust standard errors clustered at the individual are reported in parenthesis. ***, ** and * respectively indicate 0.01, 0.05 and 0.1 levels of significance.

Table A6: Change in RTI index by sector, 2006-2018

Sector	RTI change	Sector	RTI change
Libraries, archives, museums and other cultural activities	-0,735	Manufacture of wood and of products of wood and cork, except furniture; manufacture of articles of straw and plaiting materials	-0,054
Information service activities	-0,502	Manufacture of basic metals	-0,053
Scientific research and development	-0,407	Other manufacturing	-0,050
Extraction of crude petroleum and natural gas	-0,370	Remediation activities and other waste management services	-0,049
Travel agency, tour operator, reservation service and related activities	-0,358	Food and beverage service activities	-0,045
Computer programming, consultancy and related activities	-0,352	Rental and leasing activities	-0,041
Manufacture of coke and refined petroleum products	-0,308	Repair and installation of machinery and equipment	-0,036
Public administration and defence; compulsory social security	-0,305	Manufacture of other transport equipment	-0,035
Activities auxiliary to financial service and insurance activities	-0,289	Activities of membership organizations	-0,034
Creative, arts and entertainment activities	-0,283	Construction of buildings	-0,034
Residential care activities	-0,268	Manufacture of leather and related products	-0,033
Insurance, reinsurance and pension funding, except compulsory social security	-0,245	Manufacture of beverages	-0,031
Activities of head offices; management consultancy activities	-0,235	Manufacture of chemicals and chemical products	-0,029
Veterinary activities	-0,217	Manufacture of machinery and equipment n.e.c.	-0,028
Forestry and logging	-0,213	Mining of metal ores	-0,027
Undifferentiated goods- and services-producing activities of private households for own use	-0,213	Manufacture of computer, electronic and optical products	-0,023
Financial service activities, except insurance and pension funding	-0,176	Manufacture of rubber and plastics products	-0,021
Education	-0,167	Services to buildings and landscape activities	-0,021
Air transport	-0,152	Manufacture of fabricated metal products, except machinery and equipment	-0,014
Programming and broadcasting activities	-0,150	Telecommunications	-0,014
Legal and accounting activities	-0,146	Retail trade, except of motor vehicles and motorcycles	-0,012
Human health activities	-0,141	Accommodation	-0,011
Water collection, treatment and supply	-0,129	Mining support service activities	-0,009
Crop and animal production, hunting and related service activities	-0,124	Mining of coal and lignite	-0,007
Electricity, gas, steam and air conditioning supply	-0,119	Fishing and aquaculture	-0,006
Publishing activities	-0,115	Specialized construction activities	-0,006
Manufacture of other non-metallic mineral products	-0,113	Warehousing and support activities for transportation	-0,004
Water transport	-0,112	Manufacture of motor vehicles, trailers and semi-trailers	-0,003

Sector	RIT change	Sector	RIT change
Other professional, scientific and technical activities	-0,106	Manufacture of furniture	-0,001
Waste collection, treatment and disposal activities; materials recovery	-0,106	Manufacture of electrical equipment	-0,001
Manufacture of food products	-0,100	Security and investigation activities	0,001
Real estate activities	-0,098	Wholesale trade, except of motor vehicles and motorcycles	0,005
Architectural and engineering activities; technical testing and analysis	-0,096	Manufacture of textiles	0,007
Sports activities and amusement and recreation activities	-0,088	Other personal service activities	0,011
Manufacture of paper and paper products	-0,079	Land transport and transport via pipelines	0,023
Postal and courier activities	-0,079	Manufacture of wearing apparel	0,026
Civil engineering	-0,075	Wholesale and retail trade and repair of motor vehicles and motorcycles	0,045
Employment activities	-0,073	Motion picture, video and television programme production, sound recording and music publishing activities	0,054
Office administrative, office support and other business support activities	-0,072	Activities of households as employers of domestic personnel	0,067
Printing and reproduction of recorded media	-0,071	Sewerage	0,077
Advertising and market research	-0,068	Manufacture of tobacco products	0,135
Repair of computers and personal and household goods	-0,065	Social work activities without accommodation	0,177
Other mining and quarrying	-0,060	Gambling and betting activities	0,221
Manufacture of pharmaceuticals, medicinal chemical and botanical products	-0,055		

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