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Forced displacement and occupational mobility: a skills-based approach

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Abstract

We focus on mobile workers because of forced displacement and study how their occupational skills match skills in other occupations and how this commonality of skills relates to labor outcomes following displacement. Using large-scale register data from Brazil, we find that a higher occupational skills commonality shortens unemployment spells and increases the probability of transiting to another occupation. In addition, event-study analyses show that a one standard deviation increase in our measure of occupational skills commonality leads to a decrease of 1 to 3% in the probability of continuing unemployed after displacement or 10 to 20% of the overall variation in unemployment. However, although facing short periods out of the formal labor market, these individuals do not experience larger wages upon re-employment. Lastly, we explore the impact of skills mismatch on wages and find that transiting to occupations that are more similar in their skills content reduces the adverse effects of displacement.

JEL: J24, J31, J63, J65, O54

Keywords: Skills transferability; Job displacement; Occupational mobility

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1 Introduction

When facing a significant decline in the demand for their occupational skills that forces them into unemployment and to search for a new occupation because of technological change (Autor and Dorn, 2013; Braxton and Taska, 2023; Goos et al., 2014) and macroeconomic shocks (Lamo et al., 2011), workers with more specialized education profiles (Lamo et al., 2011) or more specific occupational skills (Eggenberger et al., 2022) will likely face more challenges to reallocate themselves. For example, recent evidence by del Rio-Chanona et al. (2021) shows that although dispatchers and pharmacy aides have a similar probability of automation-related displacement, dispatchers face a 21% higher increase in long-term unemployment upon automation. This significant difference is related to the fact that it is relatively more straightforward for pharmacy aides than for dispatchers to move to jobs in other occupations with increasing demand.

Researchers have long recognized the critical role played by skill transferability, highlighting its impacts on workers' movements between occupations, wages upon re-employment, and response to shocks.[1] The underlying logic is that workers can use a given set of skills to perform various tasks in different occupations, either because the same tasks are part of other jobs or because a set of skills allows for performing multiple tasks. In fact, the degree of transferability of this bundle of skills between different occupations can be reflected in an occupational commonality network (Nedelkoska et al., 2015), so that a worker's current occupation and the network of possible professions she can transition to become critical in explaining labor mobility patterns and outcomes.

This paper seeks to contribute to this literature by studying to what extent a worker's occupation position in the occupational commonality network reduces unemployment duration and affects wages upon re-employment. In doing so, we use register data for the

[1]For example, there is accumulating evidence that workers are more likely to switch to occupations with similar tasks (Gathmann and Schönberg, 2010; Poletaev and Robinson, 2008) and similar industries (Neffke et al., 2018). Moreover, longer unemployment spells result in a better match between the skills in the previous occupation and those in the new occupation (Lyshol, 2020), and unemployment exits to more distant occupations are associated with lower re-employment wages (Lyshol, 2020; Nedelkoska et al., 2015).

full population of formal wage earners in Brazil and observe workers' occupation and wage, forced displacement, and their post-unemployment occupation and wage. Using data from O*NET, we construct a measure for the occupational commonality network, i.e., the extent to which occupations share similar skills to other occupations. To account for endogenous workers' transitions, we build on the extensive literature on job displacement and use an exogenous shock resulting from firms' closures or mass layoffs.[2]

Our work relates to a growing literature studying workers' movements across occupations and the importance of the occupational commonality network in determining unemployment levels. This literature has already provided empirical evidence that specialized education reduces workers' mobility (Lamo et al., 2011), that different occupations may present substantially different long-run unemployment rates depending on their occupational commonality network (Christenko, 2022; del Rio-Chanona et al., 2021; Eggenberger et al., 2022), and that moving to distant occupations is commonly associated with lower wages (Nedelkoska et al., 2015). From a policy perspective, a better understanding of how skills in one occupation transfer to another occupation can help to support the job search of unemployed persons, especially when structural changes (e.g., automation) affect their prospects and because the unemployed narrowly focus their search activities to occupations that they are familiar with (Belot et al., 2018; Faberman and Kudlyak, 2019).

We complement this earlier work in important ways. First, most papers have relied on theoretical models or cross-sectional data without a clear exogenous identification strategy (Christenko, 2022; del Rio-Chanona et al., 2021; Lamo et al., 2011). As a result, none of these studies control for workers' unobserved characteristics and endogeneity in workers'

[2]The literature on job displacement shows that displaced workers face a significant and long-lasting decline in wages and protracted unemployment spells, with associated earning losses ranging from 3% to 25%, and that can be sustained over the long-run despite some catching up (Couch and Placzek, 2010; Eliason and Storrie, 2006; Hijzen et al., 2010; Huttunen et al., 2006; Ichino et al., 2017; Jacobson et al., 1993; Kaplan et al., 2005; Raposo et al., 2015). Furthermore, the literature defines several mechanisms when explaining the adverse effects of job loss, including the loss of firm-specific human capital that generates wage premiums (Bertheau et al., 2022; Lachowska et al., 2020), lack of bargaining power (Forsythe, 2020), unemployment stigma (Biewen and Steffes, 2010)[3], and skills transferability and the loss of occupational-specific knowledge (Becker, 1962; Gathmann and Schönberg, 2010).

transitions. In contrast, we use matched employer-employee register data that allows us to build a sample of workers that experienced displacement. Although our measure of the average distance between occupations is similar to Eggenberger et al. (2022), we focus on displaced workers because of mass layoffs or firm closures, which allows us to better control for endogeneity in occupational switching and workers' sorting into occupations. Second, while Nedelkoska et al. (2015) focus mainly on the effect of occupational distance on workers' outcomes and Eggenberger et al. (2022) focus on the effects of demand shocks on the returns to specific skills, we deepen our understanding of workers' ability to transition to different occupations, as a function of how specific their skills are to their last occupation before displacement. In so doing, our focus goes beyond education (Lamo et al., 2011) as we use the O*NET database, which provides more detailed information on the knowledge, skills, and abilities associated with different occupations. Third, we offer new results for Brazil, population-wise the 7th largest country in the world, thus narrowing the knowledge gap in estimating the importance of skill mismatch and the occupational commonality network for a middle-income country.

To advance some of the main findings, our estimates suggest that workers previously employed in occupations with a stronger occupational commonality network suffer shorter periods of unemployment. We also show that workers in occupations with a stronger network to other occupations are more likely to switch occupations following the displacement. In our preferred estimates, a one standard deviation increase in our measure of occupational commonality leads to a decrease of 1 to 3% in the probability of continuing unemployment after displacement. In addition, we examine the effects of skill mismatch on wages by exploring the similarity between occupations before and after the displacement. Our estimates indicate that moving to more similar occupations significantly reduces the adverse effects of displacement and that the negative impact increases with the distance between occupations.

The structure of the remainder of the paper is as follows. Section 2 discusses our data set, the measure of occupational commonality, and the sample restrictions. Section 3 describes the empirical strategy, while Section 4 provides the main results. A final section concludes.

2 Data

2.1 RAIS employer-employee data

To examine the impact of workers' occupations on moderating the adverse effects of displacement, we use the RAIS database (Relação Anual de Informações Sociais) from 2006 to 2018. This is a high-quality census of the Brazilian formal labor market with over 40 million contracts per year.[4] The census includes all establishments nationwide with at least one registered worker. Establishment information includes fiscal identification number (which identifies the company and the establishment across time)[5], industry sector, legal nature, and full address. At the level of individual workers, the data set includes information on workers' gender, age, education, wage, employment status, type of contract, tenure, hiring and end date, and the occupation related to the contract. The occupation is registered according to the 2002 Brazilian Code of Occupations (CBO), a detailed 6-digit code that follows a pyramid structure, with the first 2 or 4 digits representing a higher level of aggregation. In addition, the database has an individual identifier that allows us to follow individuals for the entire period.

2.2 Job Displacement and Sample-Selection Criteria

We define two types of displacement: displacement because of firm closure and displacement because of mass layoffs. Firm closure is identified when an establishment identifier ceases to exist. For mass layoffs, we follow the extensive literature on job displacement (for instance, Blien et al., 2021; Hijzen et al., 2013; Raposo et al., 2015) and define mass layoffs when 30%

[4] While excluding the informal labor market may limit the conclusions of the study given that the country has an informality rate that averaged 40.3 percent during the period of analysis, the sample selection required to observe displacement focuses on regions with a higher formality rate. These regions are also more dynamic, with a broader range of industries and occupations available in the labor market.

[5] We refer to establishments and firms interchangeably.

or more workers are displaced 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 exploit the data to the best of our capacity to exclude cases in which downward trends in employment were already perceived in the years before, possibly leading to negative selection of workers with few outside options, or when employment recovers in the years following, which would be indicative of a temporary shock and not a structural one. Additionally, some of these events might not be actual closures. Because of mergers between firms or splits of establishments, this procedure could fail to capture only closures and mass layoffs. To deal with this, 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.

We focus on workers facing job displacement between 2009-2013 and observe workers' outcomes three years before and five years after the layoff. We focus on long-tenured individuals, imposing that displaced workers must be employed in the same firm for at least three years before displacement. In addition, we restrict our sample to full-time prime-age workers, thus drawing from a sample of individuals older than 25 or younger than 50 years in the first year of analysis.[6] We also restrict firms' size, focusing on firms with at least 30 employees in the first year before displacement.

Table 1 presents some descriptive statistics of the resulting sample. We manage to identify 308,683 individuals that face job displacement, of which 30% are women and 11% have a college degree. On average, workers are 37 years old with over 7 years of experience. In addition, most workers are employed in the services sector and in the Southeast region of Brazil, the country's most populous and wealthiest region.

[6] Some individuals might have numerous jobs in a given year. We restrict to one observation per worker-year by choosing the highest-paying in any given year.

Table 1: Descriptive statistics

	Mean	SD
Average wage (BRL)	2043.39	2485.33
Worker's age	37.00	6.38
Tenure (months)	85.80	53.76
Firm's size	886.81	1359.82
Gender (Female = 1)	0.30	–
Illiterate or primary	0.04	–
Primary school graduate	0.16	–
Middle school graduate	0.22	–
High-school graduate	0.47	–
College degree	0.11	–
Agriculture and Extractive	0.04	–
Manufacturing	0.42	–
Services	0.54	–
North	0.04	–
Northeast	0.16	–
Southeast	0.58	–
South	0.14	–
Central-West	0.07	–
Observations	308,683	

The table shows descriptive statistics for displaced individuals in the year before displacement.

2.3 O*NET data on skills

A critical part of our analyses is the use of granular information on the use and intensity of knowledge, skills, and abilities across different occupations. To this end, and given the lack of information specific to the Brazilian labor market, we exploit the O*NET database. The data is a US database that aims to explain the anatomy of occupations (Peterson et al., 1999), and it is widely used to characterize the structure of employment and earnings in the US (e.g., Acemoglu and Autor (2011)) and other countries (Arntz et al., 2016), as well as to explore occupational mobility in various labor markets (Huckfeldt, 2018; Lyshol, 2020; Nedelkoska et al., 2015). In addition to other characteristics, O*NET associates a series of tasks (332), tools (4302), and knowledge, skills, and abilities (123) with each occupation. It is updated periodically and is currently in its 24th version. In each round of updates, experts (workers of a given occupation and their managers or human resource specialists) are interviewed and asked to describe what they do, how often, what they need to know, and how crucial it is for their job. We focus on knowledge, skills, and abilities (or KSA), as the literature considers that they are what workers apply, using tools or not, to perform tasks in their jobs (Nedelkoska et al., 2015).

Although O*NET is based on the American labor market, the similarity between two occupations based on O*NET's KSA is a good predictor of workers' mobility in Brazil (Gukovas, 2023). Gukovas (2023) finds that Brazilian workers are 3.1 times more likely to move between occupations on the 95th percentile of similarity than on the 5th. Therefore, we take O*NET as our instrument to identify occupations' similarities and match the O*NET to the Brazilian code of occupations (CBO), using a cross-walk with the US Bureau of Labor Statistics' occupational classification (SOC) and taking advantage of the similar structure of both classifications (Maciente, 2012).[7]

2.4 Similarity between occupations

To estimate how central a given occupation is in the network of occupations, we first build a similarity measure between each pair of occupations by calculating a Jackard Similarity Index (JSI)[8] as follows:

$$JSI_{ij} = \frac{HC_i \cap HC_j}{HC_i \cup HC_j} \tag{1}$$

where HC_i is the human capital associated with occupation i and HC_j is the human capital associated with occupation j. In our case, we consider the different dimensions of KSA from the O*NET database as human capital in the form of dummies. The O*NET classifies each dimension into seven levels, ranging from the most basic to the most advanced level

[7]Out of the 2,320 occupations in RAIS, 2,101 can be mapped to 688 occupations in O*NET. For occupations where there is a more than one-to-one match between O*NET and RAIS, we take an average of each KSA dimension weighted according to the number of workers on each in the United States labor market. Moreover, given that several CBO at the 6-digit level are matched to the same occupation in O*NET, we keep the final sample at the 4-digit level by taking the average among the 6-digit level occupations that belong to the same 4-digit level group, weighted by the number of workers in each labor market. In most of these groups, all 6-digit level occupations corresponded to the same O*NET occupation, not changing the values used.

[8]As opposed to measures based on co-occurrence, the JSI is not impacted by the number of skills of a given occupation, while when compared to correlations, it is more impacted by the presence, rather than the absence of skills in an occupation.

of knowledge. For example, suppose we aim to compare mathematics knowledge between economists and rocket engineers. We first breakdown this dimension into six levels ([0,1],]1,2],]2,3],]3,4],]4,5], and]5,7][9]. If economists use mathematics at level 3, we consider the first three breakdowns as 1, and the remaining as zero. In contrast, if rocket engineers use mathematics at level 7, all the six breakdowns will have a value of 1. In turn, if mathematics were the only dimension relevant for both occupations, the JSI would equal 0.5.

While the JSI gives the distance between each pair of occupations, we want to observe the worker's position concerning all other occupations in the market in which they supply their labor. For this purpose, and similar to Eggenberger et al. (2022), we calculate the average distance of the worker's occupation at the time of displacement to the others weighted by the log of the number of contracts active at the end of the year in the region (the mesoregion, similarly to Loyo (2016)). We call this measure the Occupational Commonality Index (OCI):

$$OCI_{imt} = \sum_{j=1}^{N} JSI_{ij} \frac{L_{jmt}}{L_m t} \tag{2}$$

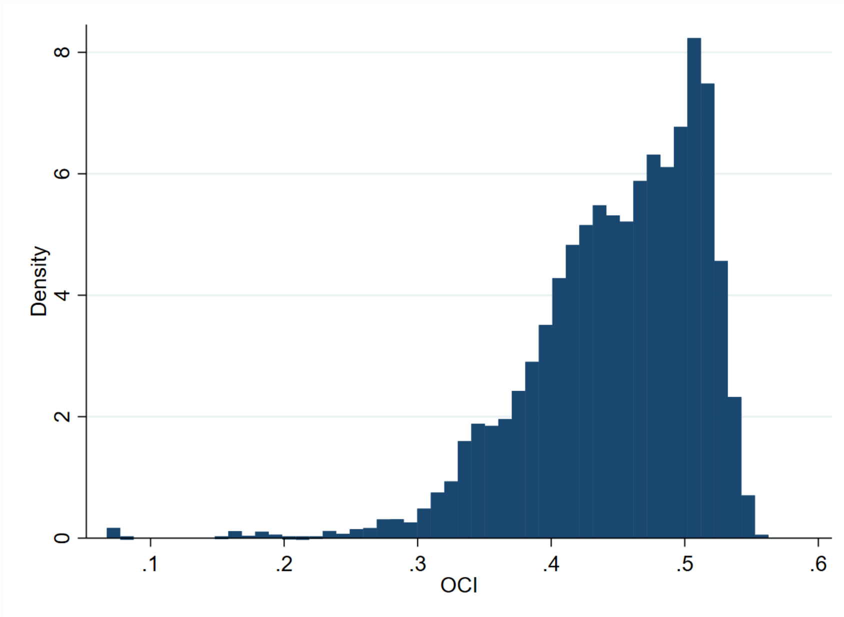
where OCI_{im} is the occupational commonality index of occupation i in the mesoregion m. JSI_{ij} is the distance between occupation i and j, and $\frac{L_{ijmt}}{L_m}$ is the relative employment of occupation j in mesoregion m and year t to weight the skill distances by the number of alternative jobs available to a worker.[10] Figure 2 presents the resulting distribution of the OCI. The left-skewed distribution ranges from around 0.06 to 0.6, which indicates that occupations share, on average, 6 to 60 percent of their skills with the other occupations available in the mesoregion. The average OCI is 0.44, and the standard deviation is 0.06. In addition, Table 2 indicates that models and telemarketers are among the most specific occupations. At the same time, construction supervisors and packaging and labeling workers

[9]There are very few occupations that use a skill with a level higher than 6; therefore we aggregate the last two levels. Furthermore, to reduce the noise caused by dimensions used by most occupations, we exclude those used by more than 95 percent of them

[10]In practice, for each worker, we measure the index for the year of displacement and the mesoregion of the previous employer. Furthermore, we calculate the relative employment by taking the logarithm to reduce dispersion and account for occupations with few (or too many) workers in the same region.

supervisors are the occupations with the largest OCI.

Figure 1: Distribution of the OCI



The figure shows the distribution of the OCI for the year 2020 across mesoregions.

Table 2: Rank of occupations with low and high OCI

Occupation	OCI	Rank
Low OCI		
Models	0,0731	1
Workers in the tasting and classification of grains and the like	0,1669	2
Telemarketers	0,1878	3
Domestic workers in general	0,2374	4
Garment sewing machines operators	0,2610	5
High OCI		
Construction supervisors	0,5443	1
Packaging and labeling workers supervisor	0,5441	2
Forestry technicians	0,5410	3
Road transport technicians	0,5395	4
Pointers and lecturers	0,5394	5

3 Empirical approach

Following a layoff, individuals can experience extended periods of unemployment, which are commonly linked to differences in workers' characteristics (e.g., gender, age, education, reservation wage, and spouse's employment status and income) (Hoffman, 1991) and labor market conditions (e.g., business cycle, local labor demand) (Wilke, 2004). We focus on whether the extent to which the skills in one's occupation before displacement link to other occupations can explain workers' re-insertion in the labor market. Specifically, we test the extent to which post-displacement employment is related to workers' skills commonalities in the previous occupations (OCI), and the extent to which the skills commonalities in one's occupation relate to occupational switches post-unemployment. In doing so, we explore firms' mass layoffs or closure as an exogenous shock to workers' careers and estimate the following specification:

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

where y_{it} is the outcome of interest (relative employment and occupational switching). Relative employment is defined as a worker's number of months employed compared to $t-2$. In addition, occupation switching is a dummy equal to 1 if the worker switches occupations (defined at 2 digits level). ν_t represents time-to-displacement dummies, from three years before the event to five years after it (t-2 is the baseline). λ_i represents individual fixed effects and capture permanent unobserved individual characteristics. σ_j and δ_s represent the structural region and sector effects, and β_k reflects the effect of the displacement on workers' relative employment. θ_k is our main outcome of interest and measures the additional effect in a specific year due to an increase in the occupational commonality index. The OCI is calculated at $t-1$ and is, therefore, based on workers' occupation at the moment of displacement. Furthermore, we standardize the OCI with a mean of 0 and a standard deviation of 1.

Finally, we also explore the effects of occupational mismatch on workers' wages. Although the OCI is more suitable for understanding an occupation's position within the network, the JSI is better equipped to measure the similarity between two occupations (A and B) and thus provides a more suitable framework for evaluating occupational mismatch after the transition. We assess the relationship between wages and the JSI by estimating the following equation:

$$log(wage) = \lambda_i + \sum_{k=-3,k\neq-2}^{5} [\nu_t^k \beta_k + \nu_t^k JSI\theta_k] + \delta_s + \sigma_j + \epsilon_{ijst} \quad (4)$$

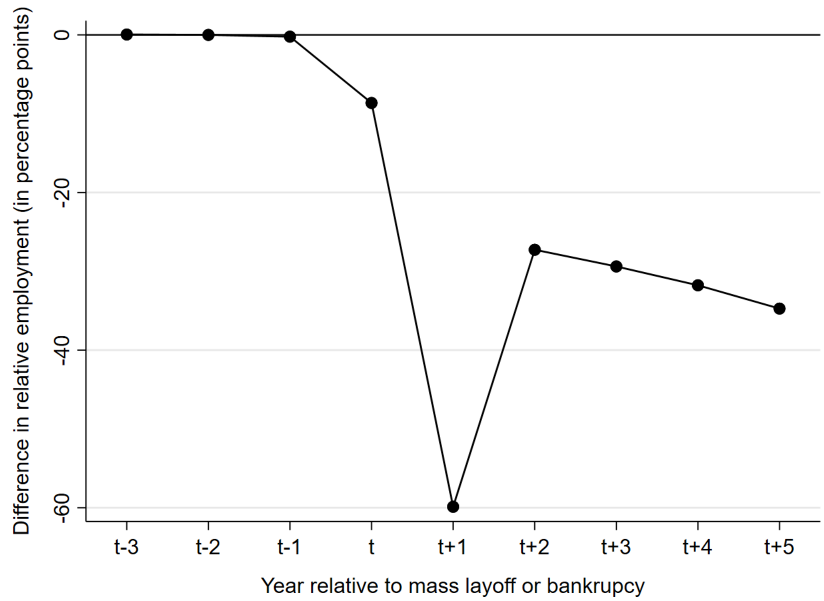
where $log(wage)$ is the logarithm of monthly wages, and the JSI captures the distance between the occupation before displacement and the first job following the event.

4 Results

4.1 Employment

We now provide baseline estimates of job displacement's impact on relative employment. Figure 2 plots the coefficients of the time-to-event dummies from Equation 3. In years before the layoff, given that workers were employed full-time, the coefficients are equal to zero by construction. However, following the event, treated individuals worked about 10% less in t and almost 60% less in the year following the event. This negative impact continues over the medium run, although the negative impact on employment reduces significantly to about 25% in $t+2$ and 35% in $t+5$ (see Table A1 in the Appendix).

Figure 2: Effect of displacement on employment

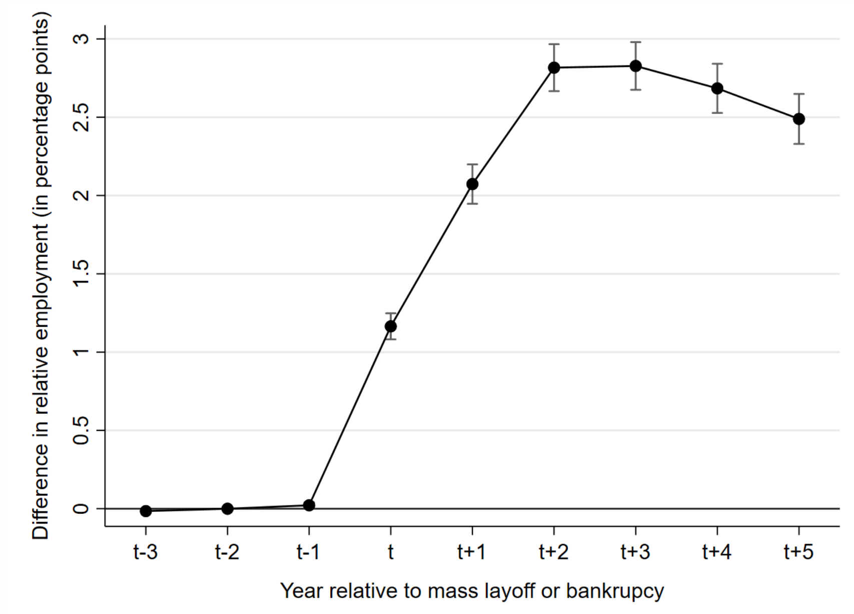


The figure shows the estimates of time-to-displacement dummies from a regression including region, sector, and individual fixed effects. The dependent variable is relative employment. Relative employment measures workers' number of months employed in a given year compared to full employment in $t-2$. Year $t-2$ is the base year. Vertical bars show the estimated 95% confidence interval based on standard errors clustered at the individual level.

4.2 Skills commonalities and employment

We are particularly interested in whether the OCI also correlates with shorter periods of unemployment. Figure 3 provides the coefficients of the interaction between time-to-displacement dummies and the OCI. The results suggest that an increase of one standard deviation in the OCI increases almost 1% in relative employment in t and over 2.8% in $t+2$ and up to five years following displacement (see Table A1 in the Appendix). Interestingly, not only does the size of the coefficient increases with time, but the share of relative employment explained by the OCIs increases too. This is consistent with the hypothesis that workers initially search for similar occupations before broadening the set of jobs they consider (Belot et al., 2018). It is also interesting to note the correlation between the coefficients in Figure 4 and Figure 3, as both the probability of switching occupations and reducing unemployment increases with time.

Figure 3: Effect of occupational commonality on relative employment

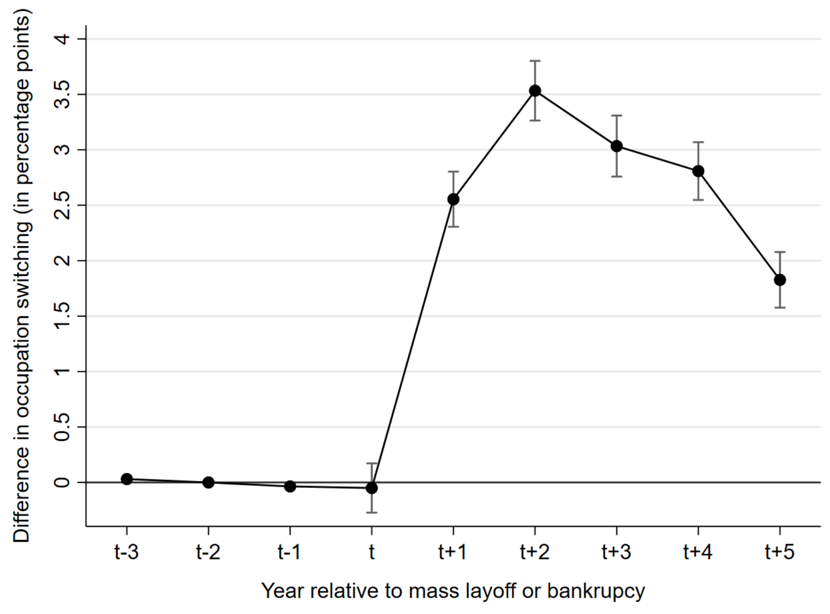


The figure shows the estimates of the interactions between time-to-displacement dummies and an occupational commonality index from a regression including time-to-displacement dummies and individual, region, ande sector fixed effects. The dependent variable is relative employment. Relative employment measures workers' number of months employed in a given year compared to full employment in $t-2$. Year $t-2$ is the base year. Vertical bars show estimated 95% confidence intervals based on standard errors clustered at the individual level.

The fact that workers initially search for similar occupations before broadening their job search is illustrated by Figure 4. The figure plots the coefficients of the time-to-displacement dummies interacted with the OCI index, taking job switching as the dependent variable. It shows that a higher OCI is indeed associated with a higher probability of switching occupations following displacement. For instance, an increase of one standard deviation in the index increases workers' probability of switching occupations by over 2.5% in $t+1$ and 3.5% in $t+2$ (see Table A1 in the Appendix). Interestingly, we find a non-significant coefficient at time t, likely related to the fact that workers first try to find jobs in the same occupation before broadening their options.

To illustrate the type of occupational transitions that we observed, we refer the reader to the Appendix, that shows most and least common transitions between the worker's previous and the first occupation after the displacement, based on JSI. Table A2 shows the most

Figure 4: Effect of occupational commonality on the probability of switching occupations



The figure shows the estimates of the interactions between time-to-displacement dummies and an occupational commonality index from a regression including time-to-displacement dummies and individual, region, and sector fixed effects. The dependent variable is a dummy equal to 1 if the worker switches occupations following the displacement. Year $t-2$ is the base year. Vertical bars show estimated 95% confidence intervals based on standard errors clustered at the individual level.

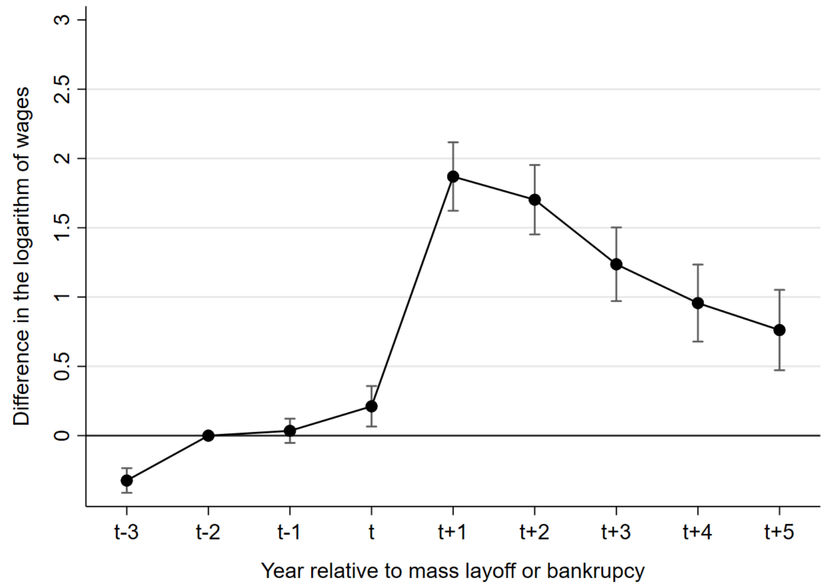
common transitions with high JSI (fourth quartile of JSI), i.e., transitions to very similar occupations. Examples of most common transitions include movements from accounting assistants to administrative assistants and from vigilantes to doormen. Table A3 describes some of the least common and more anecdotal transitions. Least common transitions are obviously related to workers moving to more distant occupations (first quartile of JSI), which include movements from cooks to electrical equipment assemblers and nutritionists and civil engineers becoming administrative workers.

4.3 Occupational distance and wages

The preceding sections primarily examined the relationship between a specific occupation and all potential labor market transitions to other more or less related occupations in terms of their skills content. Now, we focus on analyzing realized shifts from one occupation to another and assess the negative wage effects of transitioning to more distant occupations (Guvenen et al., 2020; Huckfeldt, 2018; Lyshol, 2020; Nedelkoska et al., 2015). Such negative wage effects are likely due to the loss of occupational-specific skills (Gathmann and Schönberg, 2010; ?). To assess the impact of moving to distant occupations, we focus on the JSI and estimate Equation 4. Figure 5 presents the coefficients of the interaction between time-to-displacement dummies and the JSI measure for occupational similarity. The preceding sections primarily examined the relationship between a specific occupation and all potential labor market transitions to other more or less related occupations in terms of their skills content. Now, we focus on analyzing realized shifts from one occupation to another and assess the negative wage effects of transitioning to more distant occupations (Guvenen et al., 2020; Huckfeldt, 2018; Lyshol, 2020; Nedelkoska et al., 2015). Such negative wage effects are likely due to the loss of occupational-specific skills (De Grip and Van Loo, 2002; Gathmann and Schönberg, 2010). To assess the impact of moving to distant occupations, we focus on the JSI and estimate Equation 4. Figure 5 presents the coefficients of the interaction between time-to-displacement dummies and the JSI measure for occupational similarity.

As the JSI measures the similarity between occupations A and B, the results indeed indicate that moving to more similar occupations in terms of their skill content reduces the adverse effects of displacement. For instance, a one standard deviation increase in occupation similarity increases workers' wages by about 2% in $t + 1$ (see Table A4 in the Appendix). It is interesting to note that the coefficient is larger in $t + 1$ and that there is some decline over time. We interpret this process as a result of two complementary aspects. On the one hand, as workers transition to more distant occupations, they have the opportunity to acquire new skills through learning-by-doing (Stinebrickner et al., 2019) or on-the-job training (Rica et al., 2020). This continuous skill development allows them to enhance their job performance and productivity. On the other hand, as workers gain experience and tenure on the job, firms become more knowledgeable about their abilities and potential and revise their expectations (Groes et al., 2014; Jovanovic, 1979). Both aspects positively impact workers' wages over time.

Figure 5: Effect of skill mismatch on wages



The figure shows the estimates of time-to-displacement dummies interacted with the JSI index from a regression including time-to-displacement dummies and individual, region, and sector fixed effects. The dependent variable is the logarithm of monthly wages. Year $t-2$ is the base year. Vertical bars show estimated 95% confidence intervals based on standard errors clustered at the individual level.

5 Conclusion

Job displacement has a significant and long-lasting negative effect on wages and unemployment. In explaining these findings, the literature has more recently underlined the importance of skills and occupational distance in defining workers' outcomes. Following a displacement, workers may either wait longer and move to a similar occupation or quickly move to jobs that do not match their skills. While the first option may not be realistic for many workers, shifting to occupationally distant jobs is usually associated with lower re-employment wages (Huckfeldt, 2018; Lyshol, 2020; Nedelkoska et al., 2015).

This paper uses a measure of occupational commonality to study the relationship between occupations' skill content and labor outcomes in Brazil. We explain occupational mobility from a worker's set of skills and its transferability to other occupations and show a positive and statistically significant effect on the likelihood of exiting unemployment. In our preferred estimates, a one standard deviation increase in the measure of occupational commonality leads to a decrease of 1 to 1.3% in the probability of unemployment. However, we find no significant impact on wages. We also examine the role of occupation mismatch in explaining labor outcomes. Using a measure of occupational distance between pairs of occupations, we show that moving to similar occupations significantly reduces the adverse effects of displacement on wages. Specifically, moving to similar occupations compared to more distant ones results in 1 to 2% higher wages upon reemployment.

These findings suggest several courses of action for policymakers to support displaced workers. First, for workers in occupations that have strong ties to others in terms of their skills content, intermediation services could advise them to broaden their search, thus making the best use of their less specific skill set. Most workers are biased to look for similar occupations during the first months after displacement, which could mitigate their chances of finding a new job, and broadening the search could be promising and is a low-cost intervention (Belot et al., 2018). Second, our main findings suggest that having a specific skill set significantly increases the chances of long-term unemployment and that moving to distant occupations results in higher wage losses. Therefore, public employment services should target human capital investments for workers in more specific occupations. Nevertheless, these investments are likely more effective when combined with intermediation services and unemployment insurance. Further research could explore if these policies have a different impact depending on the workers' existing set of skills.

Future research may also address the main limitations of this study: the exclusion of the informal labor market and micro and small companies and the use of skills associated with occupations as a proxy for the workers' skills. For instance, while limiting the sample to medium and large companies allowed this study to exclude potential biases, it also excluded a significant part of the labor market.[11] In addition, using skills related to occupations might not cover all the skills a worker possesses, possibly underestimating their potential re-insertion in the labor market. A dataset that links skills directly to workers and follows

[11] There could be a strong correlation between an individual worker's abilities and the firm's performance or that in small companies, workers might perform more tasks than those associated with their occupation

them in their careers could provide a more robust conclusion. Lastly, further research could also explore the robustness of our findings in different contexts, as well as heterogeneities across types of workers.

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Appendix A Appendix

Table A1: Regression estimates

	(1) Employment	(2) Employment	(3) Switch
$t-3$	0.000532***	0.000535***	-0.0000496
	(0.0000436)	(0.0000435)	(0.0000387)
$t-1$	-0.00219***	-0.00219***	0.000243***
	(0.0000851)	(0.0000851)	(0.0000357)
t	-0.0863***	-0.0863***	0.964***
	(0.000404)	(0.000403)	(0.00104)
$t+1$	-0.599***	-0.599***	0.446***
	(0.000651)	(0.000650)	(0.00136)
$t+2$	-0.273***	-0.273***	0.611***
	(0.000752)	(0.000750)	(0.00146)
$t+3$	-0.294***	-0.294***	0.470***
	(0.000769)	(0.000767)	(0.00151)
$t+4$	-0.318***	-0.318***	0.416***
	(0.000794)	(0.000792)	(0.00144)
$t+5$	-0.347***	-0.347***	0.366***
	(0.000816)	(0.000814)	(0.00136)
$t-3$ X OCI		-0.000150***	0.000307***
		(0.0000520)	(0.0000410)
$t-1$ X OCI		0.000219**	-0.000357***
		(0.0000964)	(0.0000310)
t X OCI		0.0116***	-0.000501
		(0.000424)	(0.00114)
$t+1$ X OCI		0.0207***	0.0255***
		(0.000642)	(0.00127)
$t+2$ X OCI		0.0282***	0.0353***
		(0.000765)	(0.00137)
$t+3$ X OCI		0.0283***	0.0303***
		(0.000777)	(0.00140)
$t+4$ X OCI		0.0268***	0.0281***
		(0.000801)	(0.00133)
$t+5$ X OCI		0.0249***	0.0183***
		(0.000815)	(0.00128)
Individual	Yes	Yes	Yes
Region	Yes	Yes	Yes
Sector	Yes	Yes	Yes
Observations	2720988	2720988	1467466
R-squared	0.507	0.508	0.576

Note: The table shows the baseline estimates for Figure 2, Figure 3, and Figure 4. The table shows the coefficients of time-to-event dummies (from $t-3$ to $t+5$) and the coefficients of the interactions between time-to-event dummies and an occupational commonality index from a regression including individual, region, and sector fixed effects. The dependent variable is employment (in columns 1 and 2), which is a dummy equal to one is the worker has any positive labor earnings in a given year, and a dummy indicator if the worker has switched occupations (column 3). Year $t-2$ is the base year. ***, ** and * respectively indicate 0.01, 0.05 and 0.1 levels of significance. Standard errors clustered at the individual level.

Table A2: Most common occupation transitions in the fourth quartile of JSI

Initial occupation	**New occupation**
Steam and utility machine operators	Operators of conventional machine tools
Accounting assistants	Agents, assistants and administrative assistants
Electricity and electromechanical technicians	Mechanical technicians in the maintenance of machines, systems, and instruments
General cargo vehicle drivers	Drivers of small and medium vehicles
Builder's laborer	Workers in waste collection services, cleaning and conservation of public areas
Drivers of small and medium vehicles	General cargo vehicle drivers
Doormen, watchmen, etc.	Vigilantes and security guards
Installers and repairers of electrical, telephone, and data communication lines and cables	Installers-repairers of telecommunications lines and equipment
Vigilantes and security guards	Doormen, watchmen, etc.
Installers-repairers of telecommunications lines and equipment	Installers and repairers of electrical, telephone, and data communication lines and cables

Table A3: Least common transitions in the first quartile of JSI

Initial occupation	**New occupation**
Cooks	Electrical equipment assemblers
Electrical, electronics, and related engineers	Shopkeepers
Footwear manufacturing workers	Drivers of small and medium-sized vehicles
Metal and alloy molding workers	Doormen, watchmen, etc.
Technicians in electronics	High school teachers
Doormen, watchmen, etc.	Banking service clerks
Secretarial technicians, stenographers and stenotypists	Telemarketers
Civil engineers and the like	Agents, assistants and administrative assistants
Professors of biological sciences and higher education health	Cashiers and ticket agents (except bank tellers)
Nutritionists	Agents, assistants and administrative assistants

Table A4: Job switching and the OCI

	Log(Wage)
$t-3$ X JSI	-0.00324***
	(0.000454)
$t-1$ X JSI	0.000348
	(0.000446)
t X JSI	0.00212***
	(0.000746)
$t+1$ X JSI	0.0187***
	(0.00126)
$t+2$ X JSI	0.0170***
	(0.00128)
$t+3$ X JSI	0.0124***
	(0.00136)
$t+4$ X JSI	0.00957***
	(0.00142)
$t+5$ X JSI	0.00762***
	(0.00148)
Individual	Yes
Region	Yes
Sector	Yes
Observations	863601
R-squared	0.885

Note: The table shows the baseline estimates for Figure 4. The table shows the coefficients of the interactions between time-to-event dummies and the JSI from a regression including individual, region, and sector fixed effects. The dependent variable is the logarithm of wages. Year $t-2$ is the base year. ***, ** and * respectively indicate 0.01, 0.05 and 0.1 levels of significance. Standard errors clustered at the individual level.

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