Essays on technology adoption and the labor market

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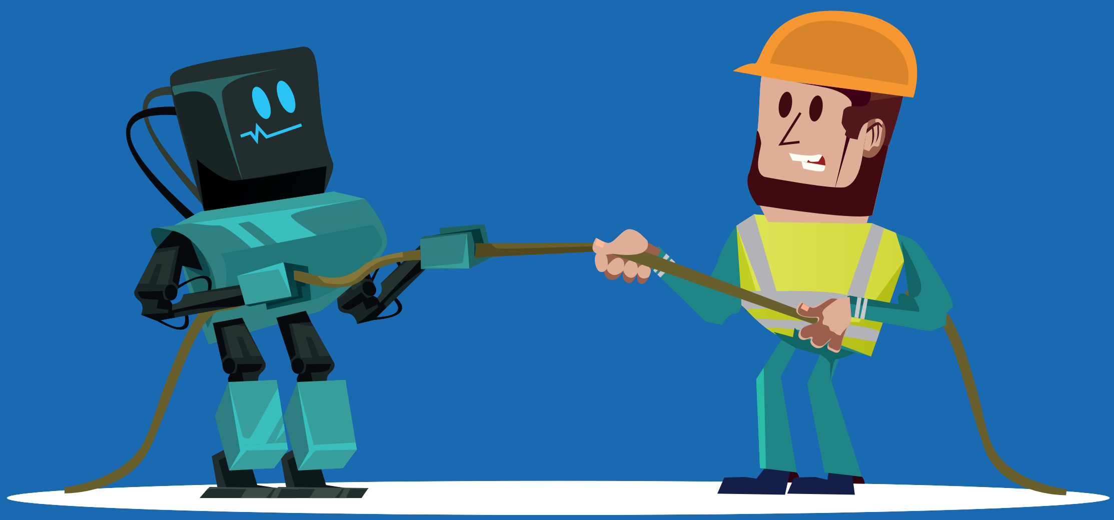
Antonio Soares Martins Neto



Doctoral thesis

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Antonio Soares Martins Neto

2024

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Dissertation

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Summary

While the benefits of technological progress are undeniable, it also brings forth numerous challenges, such as environmental degradation, political polarization, and inequality. Empirical studies have shown that technology has been a critical ingredient of economic growth and a key driver of productivity differences across firms and countries. However, there is a pressing need for more empirical studies focused on understanding the dynamics behind technology adoption and its impact on the labor market, especially in the context of developing and emerging economies.

This dissertation addresses this need by investigating the drivers of technology adoption and the links between technology and the labor market in developing economies. Chapter 2 comprehensively examines the interconnections between technology and employment in the context of developing and emerging economies, with a particular emphasis on job polarization - the relative decline of jobs in the middle of the wage and skill distribution. The results suggest that job polarization in emerging economies is only incipient compared to other advanced economies, which I argue is related to differences in technology adoption, structural change, and countries' participation in global value chains.

Despite the lack of job polarization, recent analysis suggests that there is a decline in the demand for routine jobs in emerging and developing economies. Chapter 3 empirically tests the hypothesis that, as a result of this reduced demand, the negative effect of job displacement runs differently for workers in routine-intensive occupations. We use firms' mass layoffs and bankruptcy as an external shock to workers' careers and apply a difference-in-differences model to estimate the effect of job displacement on workers' careers. Consistent with our hypothesis, the results suggest that workers in routine-intensive occupations face a more significant decline in wages and longer periods of unemployment and that the effects are larger for older and long-tenured individuals.

Older and long-tenured workers encounter more difficulties in the labor market as they find it more difficult to move to different sectors and occupations. Chapter 4 studies labor market mobility from a worker's set of occupational skills and its transferability to other occupations. We build an occupational skills commonality index and apply a difference-in-differences model taking firms' layoffs and closure as the critical event in workers' employment trajectory. The results indicate that a higher occupational commonality index leads to shorter periods of unemployment and increases the probability of switching to another occupation. In addition, we explore how skill mismatch affects workers' wages upon reemployment and find that movements to similar occupations lead to higher wages.

Chapter 5 focuses on the adoption of advanced technologies and their drivers and examines the effects of entering exporting markets on firms' adoption of more sophisticated technologies in Brazil. We combine a novel dataset on firms' adoption of specific advanced technologies with a dataset on the year they start to export. Using a difference-in-differences model, we find that starting to export is linked to a larger probability of adopting specialized software or ERP for business administration and a larger probability of adopting statistical process control with software monitoring and data management for inspection in quality control. On the one hand, the findings are consistent with a model in which exporting increases firms' complexity, and they adopt sophisticated technologies to cope with it. On the other hand, it also underlines the role of firms' interactions with buyers in reducing information asymmetries and spurring technology adoption.

In conclusion, this dissertation contributes to our understanding of the complex relationship between technology, employment, and labor market outcomes in developing economies. It underscores the need

for policymakers to foster technology adoption and design effective policies that mitigate the adverse effects of technology adoption and ensure a more equitable distribution of its benefits. The empirical evidence presented in this dissertation provides a solid foundation for policymakers to make informed decisions and design policies that promote inclusive growth and development.

Samenvatting

Hoewel de voordelen van technologische vooruitgang onmiskenbaar zijn, brengt het ook tal van uitdagingen met zich mee, zoals aantasting van het milieu, politieke polarisatie en ongelijkheid. Empirische studies hebben aangetoond dat technologie een cruciaal ingrediënt is van economische groei en een belangrijke motor van productiviteitsverschillen tussen bedrijven en landen. Er is echter dringend behoefte aan meer empirische studies die zich richten op het begrijpen van de dynamiek achter de toepassing van technologie en de invloed ervan op de arbeidsmarkt, vooral in de context van zich ontwikkelende en opkomende economieën.

Dit proefschrift voorziet in deze behoefte door de drijvende krachten achter technologie-adoptie en de verbanden tussen technologie en de arbeidsmarkt in zich ontwikkelende economieën te onderzoeken. Hoofdstuk 2 onderzoekt uitgebreid de onderlinge verbanden tussen technologie en werkgelegenheid in de context van ontwikkelingslanden en opkomende economieën, met een bijzondere nadruk op baanpolarisatie - de relatieve afname van banen in het midden van de loon- en vaardigheidsverdeling. De resultaten suggereren dat baanpolarisatie in opkomende economieën slechts beginnend is in vergelijking met andere geavanceerde economieën, wat volgens mij te maken heeft met verschillen in het gebruik van technologie, structurele verandering en de deelname van landen aan wereldwijde waardeketens.

Ondanks het gebrek aan baanpolarisatie, suggereert recente analyse dat er een afname is in de vraag naar routinefuncties in opkomende en ontwikkelende economieën. In hoofdstuk 3 wordt empirisch de hypothese getest dat, als gevolg van deze verminderde vraag, het negatieve effect van baanverschuiving anders uitpakt voor werknemers in routine-intensieve beroepen.

We gebruiken massaontslagen en faillissementen van bedrijven als een externe schok voor de loopbaan van werknemers en passen een difference-in-differences model toe om het effect van baanverplaatsing op de loopbaan van werknemers te schatten. In overeenstemming met onze hypothese wijzen de resultaten erop dat werknemers in routine-intensieve beroepen geconfronteerd worden met een sterkere daling van de lonen en langere perioden van werkloosheid en dat de effecten groter zijn voor oudere werknemers en werknemers met een lange anciënniteit.

Oudere werknemers en werknemers met een lange anciënniteit ondervinden meer problemen op de arbeidsmarkt omdat het voor hen moeilijker is om naar andere sectoren en beroepen over te stappen. Hoofdstuk 4 bestudeert de mobiliteit op de arbeidsmarkt op basis van de beroepsvaardigheden van een werknemer en de overdraagbaarheid daarvan naar andere beroepen. We stellen een gemeenschappelijke index van beroepsvaardigheden op en passen een difference-in-differences model toe waarbij ontslagen en bedrijfssluitingen de kritieke gebeurtenis zijn in het werkgelegenheidstraject van werknemers. De resultaten geven aan dat een hogere gemeenschappelijke beroepsvaardigheidsindex leidt tot kortere perioden van werkloosheid en de kans op een overstap naar een ander beroep vergroot. Daarnaast onderzoeken we hoe de onaangepastheid van vaardigheden van invloed is op de lonen van werknemers bij herintreding en stellen we vast dat een overstap naar een vergelijkbaar beroep tot hogere lonen leidt.

Hoofdstuk 5 richt zich op de toepassing van geavanceerde technologieën en de drijvende krachten daarachter en onderzoekt de effecten van het betreden van exportmarkten op de toepassing van meer geavanceerde technologieën door bedrijven in Brazilië. We combineren een nieuwe dataset over de toepassing van specifieke geavanceerde technologieën door bedrijven met een dataset over het jaar waarin ze beginnen te exporteren. Met behulp van een difference-in-differences model vinden we dat het starten met exporteren samenhangt met een grotere waarschijnlijkheid van het invoeren van gespecialiseerde software of ERP voor bedrijfsadministratie en een grotere waarschijnlijkheid van het invoeren van statistische procescontrole met software monitoring en datamanagement voor inspectie bij kwaliteitscontrole. Aan de ene kant zijn de bevindingen consistent met een model waarin exporteren de complexiteit van bedrijven vergroot en zij geavanceerde technologieën gebruiken om hiermee om te gaan. Anderzijds wordt ook de rol onderstreept van de interacties van bedrijven met afnemers bij het verminderen van informatieasymmetrieën en het stimuleren van de toepassing van technologie.

Concluderend draagt dit proefschrift bij aan ons begrip van de complexe relatie tussen technologie, werkgelegenheid en arbeidsmarktresultaten in ontwikkelingseconomieën. Het onderstreept de noodzaak voor beleidsmakers om de invoering van technologie te bevorderen en effectief beleid te ontwerpen dat de nadelige effecten van de invoering van technologie vermindert en zorgt voor een rechtvaardigere verdeling van de voordelen ervan. Het empirisch bewijs dat in dit proefschrift wordt gepresenteerd biedt een solide basis voor beleidsmakers om weloverwogen beslissingen te nemen en beleid te ontwerpen dat inclusieve groei en ontwikkeling bevordert.

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Antonio Soares Martins Neto, Maastricht, March 2024

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1
Introduction

Technology is an integral part of our lives, constantly transforming how we live and interact with those around us. Even before the history of our own species began, sharp innovative tools made of stone have eased our ancestors' lives. As time progressed, other significant technological advancements revolutionized our lives. Agriculture has changed humankind's ways of organizing, enabling settled communities to flourish. Sailing ships and the compass opened up new transportation avenues and expanded horizons, leading to the exploration of distant lands and the exchange of cultures. The printing press has transformed communication by spreading ideas and increasing literacy, antibiotics saved millions of lives, and the internet has completely modified how we interact and access information.

Many of these technologies have undoubtedly improved our lives to the extent that it is not an overstatement to say that technology and progress are closely intertwined. However, while the benefits of technological progress are undeniable, it also brings forth numerous challenges. Technological change may lead to detrimental consequences, including environmental degradation, political polarization, and inequality (Coad et al., 2021). Such progress may also disrupt existing industries and institutions, reshape firms' organizational structures, and completely modify existing occupations.

Since the 19th-century Luddite movement, economists have been particularly concerned with examining the negative impacts of technology on the labor market and the potential for widespread unemployment. As far back as 1930, Keynes (2010, p.325) highlighted that "we are being afflicted with a new disease of which some readers may not yet have heard the name, but of which they will hear a great deal in the years to come — namely, technological unemployment". Indeed, Keynes was correct in pointing out that we would frequently hear about technological unemployment in the coming years. As new waves of technological change hit the global economy, the fear of massive waves of unemployment also took place (see Vivarelli, 2007 and Vivarelli, 2014 for a review on the effects of technology on aggregate employment).

Nevertheless, rather than causing widespread joblessness, technology has more directly influenced specific groups by reshaping the demand for certain skills. Technology has exerted varying effects on different forms of labor, creating new industries and jobs, making other jobs obsolete, and significantly transforming the nature of established occupations (Buyst et al., 2018; Chin et al., 2006; Katz & Murphy, 1992; O'Rourke et al., 2013). From skilled artisans losing their jobs due to the mechanization brought by the Industrial Revolution to routine workers seeing the replacement of their jobs due to automation, technology's benefits have yet to be shared among all.

Empirically, a large literature has shown that technology has been a critical ingredient of economic growth (Aghion & Howitt, 1992; Romer, 1990) and a key driver of productivity differences across firms (Giorcelli, 2019; Juhász et al., 2020) and, consequently, across countries (Comin & Hobijn, 2010; Comin & Mestieri, 2018; Easterly & Levine, 2001). However, although the prowess of technological change is relatively well-studied, there is a need for more empirical studies focused on understanding the dynamics behind technology adoption and the labor market, and that can effectively help policymakers design better policies. As once stated by Case and Deaton (2020, p.222), "if technological change and globalization have been responsible for hurting the working class, it is not because that is what technological change and globalization must do; it is because policy was neither wise nor imaginative".

Using a series of novel datasets and applying robust methodologies, this dissertation contributes to this task by investigating some drivers of technology adoption and the links between technology and the labor market, with a particular focus on developing economies. The dissertation presents four distinct chapters, each focusing on different aspects of technology and with various policy implications.

Chapter 2 addresses an important gap in the literature and comprehensively examines the interconnections between technology and employment in the context of developing and emerging economies, with a particular emphasis on job polarization – the relative decline of middle-wage jobs in comparison to employment at the upper and lower ends of the distribution. I extensively review the existing empirical literature, study the primary drivers of job polarization, and examine the main gaps in the empirical literature. The synthesis of results suggests that job polarization in emerging economies is only incipient compared to other advanced economies. I then examine the possible moderating aspects preventing job polarization, discussing the main theoretical channels.

Overall, the lack of polarization is a natural consequence of limited technology adoption, structural change, and changes in the global value chains. Developing and emerging economies lag in incorporating cutting-edge technologies into their industries, resulting in a reduced scope for job polarization within their labor markets. Similarly, many developing economies continue to industrialize and are at the receiving end of routine jobs offshored by developed economies. Consequently, industrialization and the influx of routine jobs in these regions helped mitigate the degree of job polarization within their respective labor markets.

Furthermore, the chapter identifies a number of gaps in the literature, which I address in the third chapter. Specifically, the literature review reveals that few studies have explored how individuals in more routine occupations may still face the adverse effects of technological progress, irrespective of the lack of job polarization. The necessity for more focused studies on the individual-level consequences of technology adoption on workers' careers is the focus of the third chapter.

In Chapter 3, I investigate whether, following a layoff, workers previously employed in routine-intensive occupations suffer a more significant decline in wages and extended periods of unemployment. Extensive literature has focused on the costs of displacements on wages and unemployment duration, suggesting that workers face a significant salary decline following a layoff. The likelihood of finding a job is also significantly diminished after a job loss, increasing workers' unemployment duration and reinforcing the topic's importance for policymakers (Couch & Placzek, 2010; Hijzen et al., 2010; Jacobson et al., 1993; Raposo et al., 2019). However, although job loss is a common threat, recent technological advances have spurred particular anxiety.

If recent technology advancements have shifted the demand for routine workers, they would be more prone to face longer periods of unemployment and lower wages due to displacement. Therefore, the chapter's main contribution is to empirically test the hypothesis that displacement's negative effect runs differently for workers in routine-intensive occupations. In doing so, I use a rich Brazilian employer-employee dataset and an occupation-task mapping to investigate the impact of job displacement in different groups, classified according to their tasks.

Methodologically, I estimate the dynamic treatment effects of job displacement by comparing the labor market outcomes of workers displaced by mass layoffs and firm closures, before and after displacement, with a matched control group of workers. The results suggest that workers in routine-intensive occupations face a larger decline in wages and longer periods of unemployment. Furthermore, our results indicate that individuals in routine-intensive occupations are more likely to change occupations after the shock, but those who remain in the same occupation face a more substantial decline in wages. Lastly, the loss of employer-specific wage premiums does not explain routine-intensive workers' more substantial losses.

In Chapter 4, I study labor market mobility from a worker's set of occupational skills and its transferability to other occupations. When jobs are lost due to technological change or recessions, workers are forced to reallocate and find new jobs based on their skills. Existing research recognizes the critical role played by skill transferability, highlighting its impacts on workers' movements between occupations, wages upon re-employment, and response to shocks. For example, there is accumulating evidence that workers are more likely to switch to occupations with similar tasks (Gathmann & Schönberg, 2010; Poletaev & Robinson, 2008) and similar industries (Neffke et al., 2018) and that movements to more distant occupations are associated with lower re-employment wages (Lyshol, 2022; Nedelkoska et al., 2015).

Looking at the bundle of skills associated with an occupation and how it relates to others provides a more dynamic analysis to examine labor market transitions and their impact on workers' outcomes. Therefore, this chapter's first contribution is to derive an occupational commonality index based on workers' skills and tasks based on the O*NET database. Then, using a large employer-employee dataset from Brazil and a sample of displaced workers, I apply an event-study analysis to estimate the relationship between the commonality of skills between occupations and labor outcomes following displacement. The findings reveal that a higher occupational commonality leads to shorter periods of unemployment and increases the probability of switching to another occupation. However, I find no evidence that a higher index is associated with higher wages after re-employment. Additionally, I examine the effect of skills mismatch on wages and discover that transitioning to similar occupations is associated with higher wages.

In the last chapter, I focus on understanding technology adoption patterns in Brazil. While a considerable body of literature explores the relationship between trade and productivity, little evidence exists regarding how participating in international trade influences the diffusion of technologies, especially at the firm level. Specifically, it is unclear whether more technologically advanced firms self-select into trade or if engaging in trade leads to the adoption of more sophisticated technologies.

To address this gap in the literature, I combine data from the Firm-level Adoption of Technology (FAT) survey on the adoption of advanced technologies at the business function level with data from Brazil's Ministry of Trade on exporting firms to understand whether entering exporting markets affects firms' likelihood of adopting more sophisticated technologies. Methodologically, I take advantage of recent developments in the literature and apply a difference-in-differences model with multiple periods to examine the effects of entering export markets on technology adoption.

The main results identify one of the potential channels through which exporting activities could have an impact on firms' performance – the adoption of more sophisticated technologies. Specifically, starting to export is linked to a larger probability of adopting specialized software or ERP for business administration and a larger probability of adopting statistical process control with software monitoring and data management for inspection in quality control. The results align with the scale effect channel, which posits that greater demand prompts the adoption of new technologies (Bustos, 2011). Furthermore, the findings are consistent with the existing literature highlighting how firms tend to improve their product quality when entering international markets (Alvarez et al., 2018). In response to the higher quality requirements of export markets, these firms enhance the quality of their inputs and tailor their product quality based on the specific demands of different destinations (A. D. Kugler et al., 2020; Manova & Zhang, 2012). The results indicate that as firms adapt to more demanding quality standards, they adopt more advanced technologies linked to quality control.

In summary, this dissertation contributes to understanding the complex relationship between technology, employment, and labor market outcomes in developing economies. On the country level, it provides evidence of the extent of job polarization in developing and emerging economies and an assessment of the main drivers of job polarization. On the individual level, it offers detailed evidence of the individual-level consequences of technological progress and the roles of skills commonality in explaining individuals' outcomes. Overall, it underscores the need for policymakers to design effective and imaginative policies that mitigate the adverse effects of technology adoption and ensure a more equitable distribution of its benefits. Furthermore, it provides evidence of the relationship between entering exporting markets and the adoption of more sophisticated technologies.

2

Is There Job Polarization in Developing Economies? A Review and Outlook

This chapter is based on: Martins-Neto, A., Mathew, N., Mohnen, P., & Treibich, T. (2023). Is There Job Polarization in Developing Economies? A Review and Outlook. *The World Bank Research Observer.* https://doi.org/10.1093/wbro/lkad008

Abstract

This paper analyses the evidence of job polarization - the relative decline of mid-wage jobs - in developing and emerging economies. We carry out an extensive literature review, revealing that job polarization in these countries is only incipient compared to advanced economies. We then examine the possible moderating aspects explaining this lack of job polarization. We distinguish three groups of explanations: limited technology adoption, structural change, and changes in the global value chains. Finally, we suggest new microeconomic data and empirical analyses that should be developed in order to guide evidence-based policymaking addressing those issues in developing and emerging economies.

JEL: J24, J63, O33, E24
Keywords: Job polarization; Technology adoption; Tasks; Developing countries

2.1 Introduction

The economic discipline has dedicated a great deal to the possible harmful effects of technological progress on the labor market (Card & DiNardo, 2002; Katz & Murphy, 1992; Katz & Summers, 1989; Levy & Murnane, 1992). Throughout recent history, and more famously after the Luddite movement, "technological unemployment" has been a persistent debate topic among economists, which have constantly been deliberating whether massive waves of unemployment could be around the corner.

However, the pessimistic predictions of technological unemployment have yet to come about. Technical progress didn't pave its way through unemployment but rather through changes in the demand and composition of employment. For instance, steam power led to a significant substitution of artisans for unskilled workers, favoring the transition of low-skilled workers moving out of the farms to better-paid jobs in the cities (Buyst et al., 2018).[1] In contrast, subsequent technological waves were skill-using rather than skill-saving. The Digital Revolution in the early 1980s disproportionately and positively impacted the need for skilled workers, increasing the ratio of skilled to unskilled labor in most industries (Katz & Murphy, 1992).

Not surprisingly, when most developed countries experienced increasing wage inequality in the past 40 years (Alvaredo et al., 2018), technology-related arguments were at the forefront of explaining these labor market dynamics. The skill-biased technological change (SBTC) hypothesis suggested that technology, precisely the widespread adoption of Information and Communication Technologies (ICT), increased the demand for skilled workers, as those are more capable of using these new technologies (see the review by Card & DiNardo,

[1] Chin et al. (2006) show that, in addition to skill-replacing dynamics, steam power also had some elements that were skill-biased, causing a rise in the demand for engineers. Nevertheless, as pointed out by O'Rourke et al. (2013), novel technologies were, on average, skill-saving in the early nineteenth century.

2002), and thereby causing earnings inequality to rise (Acemoglu & Autor, 2011; Goos & Manning, 2007).

For a couple of decades, the SBTC hypothesis worked well in explaining the patterns observed in the data (Machin & Van Reenen, 1998). However, it failed to explain another important labor market dynamic: in recent years, the share of high-skill, high-wage, and low-skill, low-wage occupations grew relative to those in the middle of the distribution, resulting in the so-called job polarization (Goos et al., 2009). To account for the "hollowing out" of the occupational distribution, a more nuanced analysis focused on the tasks commonly performed by each occupation to explain the so-called job polarization in developed economies. The routine-biased technological change (RBTC) hypothesis argues that computers and robots have diminished the demand for routine, repetitive tasks in production, which are more commonly concentrated among middle-earning workers. On the other hand, tasks performed by unskilled workers, such as waiters or cleaners, and skilled workers, such as managers, are not easily codified and performed by computers (Autor & Dorn, 2013; Goos et al., 2014).

Evidence of job polarization has been extensively portrayed in developed economies. In the U.S., it was first observed in Acemoglu (1999) and later rigorously analyzed in Autor et al. (2003). Beyond this first application, Goos et al. (2009) show a disproportionate increase in high-paid and low-paid employment relative to middle-paid jobs over the period 1993–2006 for 16 European countries, using harmonized data from the European Union Labour Force Survey (ELFS). Moreover, in addition to Michaels et al. (2014) and Goos et al. (2009, 2014), who find evidence of polarization for several OECD and European countries, similar results have also been individually estimated for Germany (Dustmann et al., 2009; Spitz-Oener, 2006), the UK (Montresor, 2019; Salvatori, 2018), Portugal (Fonseca et al., 2018), and Japan (Ikenaga & Kambayashi, 2016).

The observed trends in advanced economies indicate that although technological change has not induced a surge in unemployment, it threatens to raise inequality and displace routine workers. However, beyond the context of developed economies, the literature on RBTC and its consequences on labor outcomes remain relatively limited. Understanding the labor market effects of technological change also in emerging and developing economies is important, as inequality and unemployment are already exceptionally high in these contexts. The displacement of routine workers would be particularly harmful to less-educated and vulnerable groups who face more difficulties in finding another job and are more likely to transition towards low-stability, low-wage, and high-turnover occupations (Autor & Dorn, 2013; Zago, 2020). Furthermore, a growing demand for non-routine cognitive tasks would put further pressure on educational systems. In addition to fostering educational attainment, policy-makers in developing and emerging economies would need to respond quickly to the rapid changes in the demand for skills.[2]

This paper attempts to provide a broad survey of job polarization in emerging and developing countries, giving special attention to the theoretical channels that could prevent or slow down job polarization dynamics. Specifically, we stress the roles of technology adoption, structural change, and global value chain (GVCs) participation in explaining differences across countries. Finally, we highlight policy implications that arise throughout the discussion, particularly the need for better data and empirical evidence supporting policy design.[3] Our review suggests a slower pace of job polarization in most developing and

[2]Job polarization and the decline in the middle-class could also have important political implications. For instance, Birdsall (2010) suggests that the middle class is an "indispensable" force to achieve more sensible economic policy, robust and responsive political institutions, and thus more sustained growth.

[3]We restrict our analysis to the impacts of digital technologies and automation (robots) on the labor market. Automation refers to computer-assisted machines, robotics, and artificial intelligence, such that robots are a subset of automation. Recent developments in artificial intelligence (AI) make it likely that they will replace more tasks in production, with estimations suggesting that high-paying, non-routine occupations are at particular risk of displacement (Webb, 2019). Yet, due to the short evaluation time, we do not discuss the possible implications of the more recent and advanced technologies such as AI and the internet of things (IoT).

emerging economies, likely related to a significant gap in technology adoption and (or) different paths of structural change. Nevertheless, most of the literature also finds a decline in routine intensity in developing economies (a precondition for job polarization), thus indicating relevant changes in the demand for skills. In addition, we find substantial gaps in the literature, especially micro-level studies, that could significantly improve our understanding of the subject and facilitate the implementation of evidence-based policies.

The rest of this paper is organized as follows. Section 2.2 describes the empirical literature on job polarization in developing economies. Next, Section 2.3 describes possible factors moderating the effect of automation in developing economies and investigates the interactions between technology adoption in advanced economies and the labor market implications in emerging countries. Section 2.4 explores the need for more micro-level studies and discusses policy implications of job polarization in developing countries. The last section concludes.

2.2 Is there job polarization in developing economies?

Focusing on different regions and countries, as well as various measures of tasks and skills, the literature on job polarization in developing economies is gaining momentum (see Table 2.1 for a detailed summary of this literature).[4] For instance, Maloney and Molina (2019) use global census data for 67 developing countries and 13 developed

[4]Despite the growing discussion around job polarization in developing economies, one of our research's main challenges was the initial search for articles on the topic. Searching on the Web of Science and Scopus, using different keywords related to job polarization and developing economies, we identified only a few articles, for which fewer were actually about developing and emerging economies. To overcome this challenge, we have extensively relied on citations and Google Scholar to find working papers, articles, and reports, which has resulted in about 20 articles focusing on job polarization in developing and emerging economies.

economies and, although the results corroborate labor market polarization and labor-displacing automation in developed economies, the authors find little evidence of either effect on developing economies, except for Mexico and China. Das and Hilgenstock (2022) use data on 85 countries since 1990 and observe similar results. In addition, the authors propose a measure of exposure to routinization based on occupations' risk of displacement by information technologies. Using this measure, the authors show that developing economies are significantly less exposed to routinization and that initial exposure to routinization is a strong predictor of the long-run exposure.

The lack of polarization is further corroborated in Gasparini et al. (2021), who find similar conclusions for Latin America's six largest economies (Argentina, Brazil, Chile, Colombia, Mexico, and Peru), arguing that although automation has largely impacted workers in routine-intensive occupations, there is no evidence for polarization in the labor market. Messina et al. (2016) employ the Skills Toward Employment and Productivity (STEP) Surveys conducted in Bolivia and Colombia as a proxy to measure the task content of jobs in Chile and Mexico. They find few signs of job polarization, except for Chile. In fact, Brazil, Mexico, and Peru present positive growth rates for workers in the middle of the wage distribution. Beylis et al. (2020) study the labor market of 11 Latin American countries (LAC) from 2000 to 2014. Applying the methodology proposed by Autor et al. (2003) and Acemoglu and Autor (2011), the analysis shows substantial changes in the composition of occupations. Although at a different intensity, the demand for routine manual intensive tasks has declined for the entire sample, coupled with a clear and marked increase in the demand for non-routine intensive occupations. Yet, these changes in the labor composition have not resulted in polarized markets. In Central and Eastern European economies, Nchor and Rozmahel (2020) find that despite an increase in the demand for high-skill workers and a decline in middle-skill employment, the rise in low-skill employment is minimal to lead to a U-shape employment distribution which indicates labor polarization.

Even among developing and emerging economies, the evidence is not homogeneous. Hardy et al. (2016) study 10 Central and Eastern European (CEE) countries and point to an increase in non-routine cognitive tasks and a decrease in manual tasks. Nevertheless, contrary to other developed countries and at odds with RBTC, the authors also find that routine cognitive tasks increased in six CEE countries, remained stable in two, and declined in the remaining countries. Helmy (2015) studies the Egyptian labor market over the period 2000–2009 and finds suggestive evidence of job polarization, with a decline of 5.9% in the share of employment of middle-skilled occupations compared to a growth of 4.5% and 1.4% for low- and high-skilled occupations. Ge et al. (2021) use census data from China and find that the share of employment in routine manual occupations declined by 25 percentage points from 1990 to 2015. Similarly, Firpo et al. (2021) find evidence of wage polarization in Brazil, but not with respect to employment. In contrast, Fleisher et al. (2018) show that middle-skilled jobs are increasingly transitioning to work in the unskilled and self-employment job categories in China, consistent with the RBTC hypothesis. Similarly, using data from the National Sample Survey Organization from India, Sarkar (2019) also observes increasing job polarization during the 1990s and 2000s. In the period 1984–94, the author finds an upgrading pattern, with a substantial increase in the employment of high-skilled occupations. In contrast, the following periods show a polarized U-shaped employment growth, with a decline of almost 20% for occupations in the 40th percentile of the skill distribution.

Table 2.1 summarizes the main findings of this section, highlighting the context of the study: the unit of analysis, the data sources, the countries, the task measurements, and the impact of technological change on two outcomes of interest, the existence or not of job polarization and the increase of decline in the intensity of routine tasks. Except for the cases of India, Egypt, and China, most papers fail to observe job polarization in emerging and developing economies. However, as previously discussed, many articles already observe a decline in the routine intensity across low- and middle-income countries - a precondition for job polarization. For the group of papers exploring the impact on task content, all results are negative, suggesting that developing countries are less intensive in non-routine cognitive skills than advanced economies. We will explore in more detail these differences in subsection 2.4.2 and highlight the need for better measures of tasks across occupations in emerging and developing economies.

Table 2.1: Summary of the existing literature on job polarization in developing and emerging economies

Level of analysis (1)	Dataset (2)	Country (3)	Task (4)	Result (5)	Reference (6)
Impact on job polarization					
Country	Global Census Data (IPUMS)	80 developed and developing countries	Occupations	(-)	Maloney and Molina (2019)
Country	IPUMS, EULFS, household surveys	85 developed and developing countries	O*NET	(-)	Das and Hilgenstock (2022)
Country	Household surveys	Argentina, Brazil, Chile, Colombia, Mexico, and Peru	PIAAC	(-)	Gasparini et al. (2021)
Country	Household surveys	Chile and Mexico	STEP	(-)	Messina et al. (2016)
Country	Household surveys	10 Central and Eastern European countries	O*NET	(-)	Hardy et al. (2016)
Country	Household surveys	11 LAC countries	O*NET	(-)	Beylis et al. (2020)
Sectors	Egyptian Central Agency for Public Mobilization and Statistics	Egypt	Occupations	(+)	Helmy (2015)
Country	Census data	China	O*NET	(-)	Ge et al. (2021)
Country	Household surveys	Brazil	O*NET	(+/-)	Firpo et al. (2021)
Local Labor Markets	CHIP surveys	China	O*NET	(+/-)	Fleisher et al. (2018)
Sectors	National Sample Survey Organization	India	Occupations	(+)	Sarkar (2019)
Country	Household surveys	70 countries	O*NET	(-)	World Bank (2016)
Country	Household surveys	70 countries	O*NET	(-)	Aedo et al. (2013)
Country	Household surveys	70 countries	O*NET	(-)	Arias et al. (2014)
Country	European Union Labour Force Survey	Central and Eastern European countries	Occupations	(-)	Nchor and Rozmahel (2020)
Impact on task content					
Country	STEP	10 countries	STEP	(-)	Dicarlo et al. (2016)
Country	Household surveys	86 countries	STEP/O*NET	(-)	Lo Bello et al. (2019)
Country	STEP and PIAAC	42 countries	STEP/PIAAC	(-)	Lewandowski et al. (2019)
Country	Household surveys	87 countries	STEP	(-)	Lewandowski et al. (2020)
Country	STEP and PIAAC	35 countries	STEP/PIAAC	(-)	Caunedo et al. (2021)
Country	STEP	10 countries	STEP	(-)	Saltiel (2019)

Note: The table is separated into groups of papers according to the primary dependent variable in the analyses. Impact on job polarization refers to studies examining the extent of job polarization and, in most cases, without a clear chain of causality between technology adoption and polarization. Impact on task content refers to papers focusing primarily on the differences in the task content of occupations across developed and developing economies. In addition, column 2 refers to the primary occupational dataset, while column 4 describes the measurement of tasks used. Column (5) indicates the sign of the significant relationship tested in each paper, that is, the existence of job polarization (in the impact on job polarization studies), or on the intensity of routine tasks (in the impact on the task content studies).

2.3 The missing job polarization

The literature has identified three main channels driving job polarization - technology adoption, structural change, and participation in global value chains (GVCs). This section discusses how developing economies may differ from advanced ones in each of these aspects and, in turn, how that difference may explain the absence of job polarization in developing and emerging economies. For each channel, we first present the general theoretical mechanisms and then discuss the main differences observed in developing and emerging economies vis-à-vis advanced ones.

We begin by examining the role of technology adoption, focusing on why firms may have lower rates of adoption and exploring potential explanations for differences in technology choice. We then move from a micro-level to a macro-level discussion, illustrating the role of structural change and regional differences as key drivers of job polarization. Finally, we open our economy to international trade and discuss how both the micro and macro aspects of a given economy are affected by a country's participation in GVCs. Although we present each mechanism separately for the sake of simplicity, we emphasize that all of them are interacting forces. For instance, structural change and differences across sectors and regions are to a large extent a combination of firms' decisions either at the local level or a result of a country's participation in GVCs.

2.3.1 Technology Adoption

The "routinization" hypothesis argues that firms combine a continuum of tasks to produce, which can be performed either by capital or labor (Acemoglu & Autor, 2011; Autor et al., 2003). Firms will allocate more capital or labor in a given task depending on their relative cost and the degree to which tasks can be automated (repetitive and replaceable by code and machines). In the past decades, not only did the quality-adjusted ICT and robots prices fall considerably, but these technologies have been particularly successful in carrying tasks that follow explicit rules (routines) (Graetz & Michaels, 2018; Michaels et al., 2014). As a result, firms spurred the substitution of labor in routine tasks, so workers in routine-intensive occupations were suddenly at high risk of displacement. Traditionally, many routine tasks are concentrated in middle-wage, middle-skill white-collar jobs such as bank clerks, or are carried out by blue-collar less-educated workers, performing, for example, assembly tasks. As firms increase the share of capital in production, the demand for middle-earning jobs should contract, and the labor market should polarize. Yet, while ICT and other automated technologies are expected to be widespread in advanced economies, lower adoption rates can be found in developing and emerging economies. The slow pace of technological adoption in these economies may reflect many aspects, including firms' capabilities, the extent of informality, and countries' human capital endowments.

Firm behavior and capabilities

Firms' ability and willingness to adopt digital technologies are heterogeneous across and within countries. For instance, in the specific cases of Brazil and Vietnam, recent evidence suggests that most firms still rely on pre-digital technologies to perform daily tasks (Cirera, Comin, Vargas Da Cruz, Lee, & Soares Martins Neto, 2021a, 2021b). However, more than a sign of backwardness, firms' decision to not adopt more advanced technologies may be an optimal response to their small scale, local competition, and the relative price of labor and capital. Labor is substantially cheaper in developing economies, and the number of small and informal establishments with a small production scale is larger (we discuss the role of informality below). As Banerjee and Duflo (2005) point out, one reason for the lag in technology adoption could be that the firms are too small to profit from the best technologies.

Similarly, when wages are low, the relative price of investment is relatively higher (Hsieh & Klenow, 2007) and deters technology adoption. In the context of developed economies, Shim and Yang (2018) show that, in the U.S., in high-paying sectors (where therefore, the relative cost of wages compared to capital is higher), there are incentives to replace routine employment. This is confirmed by Lordan and Neumark (2018), who show that minimum wage increases are associated with a higher probability of replacing routine occupations. In other words, lower wages disincentivize firms in developing countries to adopt more sophisticated technologies.

Yet, decisions are not always optimal, and firms may simply not be aware of the available technologies. Due to restricted technological diffusion, advanced technologies have limited diffusion in developing economies - a classic example of information failure. Acquiring this knowledge can be very costly, and companies may think that adopting new practices would not be profitable (Jensen, 1988). Finally, even when managers are aware of best practices, there is a final process of acceptance and implementation. As once stated by Rosenberg (1972, p.191), "in the history of diffusion of many innovations, one cannot help being struck by two characteristics of the diffusion process: its apparent overall slowness on the one hand, and the wide variations in the rates of acceptance of different inventions, on the other".

Technology adoption also depends on firms' dynamic capabilities (D. J. Teece et al., 1997), that is, their ability to "integrate, build and reconfigure internal and external competencies to address rapidly changing environments". Therefore, the diffusion of (foreign) new technologies within developing economies also relates to firms' absorptive capacity (Cohen, Levinthal, et al., 1990) and can explain differences in knowledge spillovers and adoption behavior in firms (Fagerberg, 1994). Because of institutional and resource constraints in developing economies, firms' low absorptive capacity could be critical to explain limited technology adoption.

Informal sector

The sizeable informal sector in emerging and developing economies could also impact the patterns of job polarization. The informal sector, which accounts for 90% of the economy in developing (low-income) countries and 67% in emerging (upper-middle and lower-middle) countries (Bonnet et al., 2019), typically lags in adopting the latest technologies (Cirera, Comin, Vargas Da Cruz, & Lee, 2021), is labor-intensive and has lower productivity compared to the formal sector (La Porta & Shleifer, 2014), and most of its workers are engaged in low-skilled services and artisanal production (Falco et al., 2015). Therefore, the potential of technology-driven job displacement is likely less severe in countries with a high share of the informal economy.[5]

Moreover, technology adoption in the formal sector displaces workers toward the informal sector and, through this channel, may also affect wages there (Chacaltana Janampa et al., 2018). Using a general equilibrium model, Gomez (2021) finds that an increase in technology adoption in the formal sector results in a larger informal sector and lower wage inequality at the bottom of the skill distribution.

Availability of human capital

Human capital is an essential factor in explaining the adoption of advanced technologies within firms. For instance, using a large cross-country sample of developed and developing economies, Benhabib and Spiegel (1994) show that human capital affects the speed at which countries absorb technological developments. Comin and Hobijn (2004) examine the diffusion of more than twenty

[5]The considerable presence of informal firms in low-income countries relates to countries' capabilities and is due to the inadequate access to education but also corruption, regulation, and the lack of proactive policies to embrace the informal economy (Etim & Daramola, 2020).

technologies across developed economies and find that countries' human capital endowment is the most crucial determinant of the pace of technology adoption. As clearly stated by Boothby et al. (2010, p.621), "firms embracing new technology have to obtain new skills and/or to upgrade the skill level of their existing workforce because the attributes of new technology could be significantly different from old technologies". The literature has largely stressed the lack of managerial capabilities (Bloom & Van Reenen, 2010) and workers' skills in developing economies, which in turn are a critical constraint to innovation and technology adoption (Cirera & Maloney, 2017). Educated managers may have a greater understanding about sophisticated technologies and be favorably disposed to adopt them. For instance, using data on digital technology usage, Nicoletti et al. (2020) find empirical evidence that low managerial quality and the lack of ICT skills are negatively associated with technological adoption in 25 European economies.

2.3.2 Structural explanations: sectors, regions, and demographic change

Job polarization is a combination of within-industry and between-industry changes in employment shares, which are, in turn, affected by demographic changes and their effect on the demand for goods and services across firms, sectors and regions. In what follows, we detail how the characteristics of developing and emerging economies in terms of these different dimensions may affect their employment structure and dynamics.

Structural change

On the one hand, as technological change replaces routine tasks, a given industry will use less routine employment even while maintaining the same output levels. On the other hand, occupations' intensity in such routine tasks differs across industries, such that sectoral employment shifts also explain aggregate occupational share changes (Goos et al., 2014). In fact, Foster-McGregor et al. (2021) suggest that the risk of automation (or routine intensity) shows only modest variation within sectors and between countries, but a considerably greater variation between industries within countries. Specifically, manufacturing sectors generally demand relatively larger shares of middle-skilled, routine occupations than agriculture and services. For example, Lee and Shin (2019) find that polarization is faster in manufacturing than in services, and Bárány and Siegel (2018) indicate that job polarization in the U.S. is directly linked to the decline of manufacturing employment since the early 1950-1960s. Therefore, the level of aggregate routine intensity depends on the sectoral structure of employment — for example, we may expect that the higher the share of manufacturing, the higher the routine intensity for a given country.

What do these findings imply regarding employment dynamics in developing and emerging economies? The answer lies in the countries' trajectories. Often, low-income countries have a significant share of employment in agriculture and a small percentage of workers engaged in routine tasks in the first place. As countries become more productive in agriculture and start industrializing, they also increase their share of routine occupations. As clearly stated in Das and Hilgenstock (2022, p.100), "the observed increase in the exposure of routinization in developing economies indicates that structural transformation was greater than the offsetting impact from the declining in the price of ICT capital". Industrialization thus moderates the effects of technological change on the demand for routine labor. Overall, Das and Hilgenstock (2022) show that labor markets in low- and middle-income countries are significantly less exposed to routinization (lower share of routine-intensive occupations), reflecting the larger share of agriculture in developing economies. In contrast, in more advanced stages of development, countries transition from manufacturing to services and job polarization accelerates.[6]

[6] A similar explanation relates to the wage structure. The decline in the demand for routine-intensive occupations only leads to job polarization if these occupations

Heterogeneity across sectors and regions

Much of the literature presented above has relied primarily on aggregate measures, and thus somewhat overlooked job polarization's regional and sectoral heterogeneities. It remains unclear if the slow pace of polarization in most developing and emerging economies is a general trend or is confined to a few sectors or regions within countries. Some related evidence can be found for developed economies. Using individual-level data from Statistics Sweden from 2002 to 2012, Henning and Eriksson (2020) find that the decline in manufacturing employment in clusters of previously manufacturing-dominated municipalities drives polarization in the country. In contrast, areas with fast-growing firms in sectors with larger shares of routine workers (extraction industries and lower manufacturing) exhibit the opposite patterns, indicating a greater tendency towards job upgrading.

Regional and sectoral differences, and more specifically, the role of extractive industries, could therefore help to explain the modest evidence of job polarization in some emerging economies.[7] The

are in the middle of the wage distribution and if the wage distribution reflects the skills structure. Nevertheless, routine occupations in emerging economies could be ranked differently, given the sizeable informal sector and wage-setting institutions. For example, using data from 10 OECD countries, Haslberger (2021) documents that RBTC can lead to occupational upgrading rather than polarization, as countries differ in terms of the occupational routine-wage hierarchies. In other words, given that in many developing countries, the number of workers engaged in codified tasks is small and, in some cases, concentrated in low-wage occupations, routinization could lead to occupational upgrading.

[7] Besides differences across sectors, firms of the same industry also present considerable heterogeneity in their employment and wage structures (see Helpman et al., 2017 for Brazil and Domini et al., 2022b; Harrigan et al., 2020 in the case of France). In the context of developing countries, it could be the case that there is a polarization process within firms, but it is compensated by the fact that large and growing firms are more intensive in middle-earning occupations. Therefore, reallocation dynamics (i.e., changes in the market shares of firms within sectors) among firms with different occupational structures may explain why occupational shares at the

commodity boom in the early 2000s led to a significant expansion of the extractive sector in many countries, which is likely to offset the decline in middle-earning jobs across other sectors. Indeed, in many Latin American and African economies, the commodity boom experienced during the 2000s mainly favored low-skilled workers, potentially overshadowing the impacts of ICT adoption (Maloney & Molina, 2019).

Demography

Finally, differences in demographic dynamics across developed and developing economies affect changes in the demand for goods and services as well as the supply of work, therefore resulting in diverging patterns of overall employment. Moreno-Galbis and Sopraseuth (2014) show that population aging in developed economies leads to a rise in the demand for personal services, causing an increase in the employment share of low-paid positions. For instance, population aging leads to a rise in the demand for jobs such as cleaners, transportation services in the health industry, and housework employees in private homes. In addition, Acemoglu and Restrepo (2021) find that population aging results in a shortage of middle-skilled workers, thus increasing the adoption of automation technologies. However, this pattern contrasts with the demography in most emerging economies. Especially in Africa, countries are experiencing significant growth in the working-age population, resulting in a less intense demand for low-paid occupations and an abundance of middle-skilled workers.

2.3.3 Employment dynamics in open economies

Most of the literature on job polarization in developing countries has relied on isolated analysis at the country level without considering

aggregate level do not change.

possible effects stemming from changes in global value chains. The effects of GVCs on job polarization in developing economies are not straightforward. Technological development has drastically reduced the costs of offshoring jobs to locations with lower labor costs, such that firms in developed economies have off-shored routine-intensive occupations (Acemoglu & Autor, 2011; Blinder & Krueger, 2013; Goos et al., 2014). In turn, the inflow of routine jobs from advanced countries has likely reduced polarization forces in some host countries (Maloney & Molina, 2019).

At the same time, new advancements in robotics have reduced the prices of these technologies substantially, resulting in developed economies re-shoring part of their production. The rapid spread of robots in advanced economies could thus have the opposite effect, likely reducing the share of routine workers and accelerating job polarization in developing economies. Krenz et al. (2021) develop a theoretical model to account for these interactions in which automation in advanced countries increases productivity and reduces the costs of producing in-shore. As a result, part of the production that was previously off-shored to host areas in developing regions may return, although not leading to an improvement in wages for low-skilled workers or the creation of new jobs in the receiving economies.

Below, we examine these two contrasting forces affecting job polarization in developing economies. We first highlight the initial findings pointing to the role of offshoring in mitigating job polarization in developing economies. We then point to more recent evidence about the effects of re-shoring and conclude by discussing the specific case of multinationals (MNEs).

Global Value Chains and the routinization of tasks

Early studies on the interactions between global value chains (GVCs) and job polarization pointed to different trajectories between developed and developing economies. For instance, Das and Hilgenstock (2022) show that the participation in GVCs might have played a role in the rising number of routine jobs in developing economies while reducing it in advanced economies. Similarly, Reijnders and de Vries (2018) explore the impacts of both technological change and offshoring on the labor market for several developed and emerging economies. Although the results corroborate an increasing share of non-routine occupations in the labor market of both groups, the authors find that the effect of task reallocation via offshoring reinforces the decline in routine jobs for advanced economies and mitigates it for developing countries. In addition, Lewandowski et al. (2019) test the association between the routine-intensity of occupations and technology (computer use), globalization (specialization in global value chains), structural change, and supply of skills in 42 countries at different stages of development. The results generally corroborate the main drivers of job polarization. On the one hand, technology, structural change, and the supply of skilled workers are positively correlated with routine intensity. On the other hand, globalization is positively associated with routine intensity in developing countries and negatively in developed countries, reinforcing the argument that developed countries are offshoring routine occupations to host countries. Finally, Lo Bello et al. (2019) study both supply (e.g., education, age, and age structure) and demand (growth, sector structure, technology, and trade) factors in explaining differences in the skill content of jobs and find that technology adoption is related to de-routinization and trade is an offsetting force in developing economies.

New trends: Reshoring, robot adoption, and job polarization

Recent findings show that automation may be linked to reshoring or decreased offshoring, implying decreasing employment in developing economies.[8] Krenz et al. (2021) explore 43 countries and nine manu-

[8]Although some evidence suggests that automation in advanced economies is yet to

facturing sectors and provide evidence that robot adoption increases re-shoring activity. Similarly, Kinkel et al. (2015) analyze 3,313 manufacturing firms in seven European countries and find empirical evidence that firms using industrial robots are less likely to off-shore their production outside the region.

Without focusing on offshoring per se, a recent strand of the literature also shows that robot adoption in developed economies negatively impacts wages and employment in developing economies. Using data from Mexican local labor markets between 1990 and 2015 and the International Federation of Robotics (IFR), Faber (2020) shows a negative impact of robot adoption on Mexican employment, with a more substantial effect for women and low-educated machine operators in the manufacturing sector. Also exploring the Mexican labor market, Artuc et al. (2019) show that an increase of one robot per thousand workers in the U.S. lowers growth in exports per worker from Mexico to the U.S. by 6.7 percent. However, the authors didn't find evidence of an impact on wage employment or manufacturing wage employment. A. D. Kugler et al. (2020) use data from the International Federation of Robotics (IFR) to measure automation in the U.S. and microdata from the Colombian Social Security records to examine the effects of robot adoption in the U.S. in the Colombian labor market. The results indicate a negative impact on the employment and wages of Colombian workers, especially for women, older and middle-aged workers, and workers employed by SMEs.[9]

The role of MNEs

The literature has yet to examine the role of MNEs as drivers of job

impact FDI flows (Hallward-Driemeier & Nayyar, 2019).

[9] In addition to changes in world trade, the COVID-19 pandemic may also have had an impact on the pace of digital adoption in developing economies. While initial evidence suggests that the pandemic has accelerated the digital transformation of businesses, it also indicates widening the digital divide(Avalos Almanza et al., 2023).

polarization in emerging economies. An extensive literature has already provided evidence that MNEs are more productive (Helpman et al., 2004), pay higher wages (Hijzen et al., 2013), and employ a higher share of non-routine jobs (Hakkala et al., 2014). In this context, an increase in foreign direct investment (FDI) could have implications for job polarization in host economies. For instance, Olsson and Tåg (2017) examine the impacts of private equity acquisition on the employment composition of recently acquired firms in Sweden and finds that workers in less productive firms in routine-intensive occupations are twice more likely to be displaced after buyouts. In the specific case of FDI, Hakkala et al. (2014) rely on Swedish data to study changes in firms' ownership and find that MNEs demand more non-routine tasks or tasks requiring personal interactions compared to their local counterparts. In addition, Amoroso and Moncada-Paternò-Castello (2018) use data on greenfield FDI for several European economies to examine the extent to which different types of FDI are related to job polarization. They find that low-skill FDI investments are associated with skill downgrading, while skill-intensive FDI is more commonly associated with skill upgrading. Only investments in ICT are related to job polarization.

Yet, as for developing economies, the overall impact on the labor market will depend on many factors. In addition to the current economic structure and the target sectors (either low-skill or skill-intensive), the impacts of FDI also rely on foreign firms' ability to spur technology adoption. Changes in ownership and the increasing share of MNEs in already established sectors could have different impacts. For instance, extensive literature has pointed out MNEs' role in transferring technology and managerial skills (for example, D. Teece, 1977). In this context, if MNEs catalyze technology adoption across local firms, job polarization could emerge as an overall effect of more extensive technology diffusion. In contrast, a different strand of the literature stresses that MNEs are more likely to crowd out local firms, use technology that is inappropriate for local circumstances, and limit technology transfer (Oetzel & Doh, 2009). As a result, job polarization would be limited to a few MNEs, and the extent of polarization would depend on MNEs' share in total employment.

Taking stock

Our literature review indicated a significant decline in routine intensity in many developing economies, although with little evidence of job polarization. In addition, section 2.3 has explored the reasons for such a lack of polarization in (most) emerging and developing economies and has highlighted some of the main gaps in the literature. We have stressed the need for empirically examining the main drivers of the slow pace of polarization, including countries' participation in GVCs.

A critical argument in our discussion is that structural change and GVC participation can counterbalance the effects of technology adoption on labor demand for routine tasks in emerging and developing countries. Yet, we do not have empirical evidence on this particular process. Also, the observed differences across countries, also at a similar level of income or technological knowledge, raise many questions and suggest that further evidence should explore more disaggregated information. For instance, is there within-sector polarization in low- and middle-income countries? Has the process of industrialization curbed the aggregate routine intensity among those economies? Did occupations become less intense in routine tasks over time? Lastly, has the falling demand for routine tasks negatively impacted workers?

Answering these questions (and many others) can significantly impact the development of better-adapted technological, educational, and labor market policies. The following section discusses the opportunities and challenges associated with technology policies in developing and emerging economies and the implications in terms of employment patterns and policies.

2.4 The need for more studies based on microdata to guide policymaking

As mentioned by Case and Deaton (2020, p.261), "[G]lobalization and automation are ultimately beneficial, but they create disruption, especially in the short run, and many less skilled workers lose out." This conflicting impact of technology poses additional challenges to policymakers, highlighting the need for complementarity in public policies. For instance, while encouraging and facilitating technology adoption, labor market de-routinization calls for robust social protection systems to help workers with low job mobility, especially more disadvantaged groups. For instance, Lewandowski et al., 2017 study the intergenerational disparities in the de-routinization of jobs in 12 European countries and find a significant relationship between age groups and shifts in the task composition. The decreasing demand for routine occupations also challenges existing education and training systems to respond to changing skill demands, especially given the fact that low-educated workers are commonly more affected by the routinization process (Martins-Neto et al., 2022). It is crucial to adequately equip the labor force with the necessary skills to guarantee maximum benefits from recent technological advancements, stimulating the development of competencies with increasing demand - an excellent example of this is the soft-skills training for employees in the hotels and accommodation industry (for instance, the training from Quality Assurance Agency, 2015 in the UK).

Ultimately, designing better-fitted policies for skill development, such as programs up-scaling digital skills, vocational training, and better-adapted social protection systems, requires detailed microeconomic studies. Researchers need to move from aggregate measurements of polarization into micro-level information to examine differences across firms and workers, including assessing workers' ability to transition from displacement to re-employment in high-paying jobs in different institutional contexts. This calls for more systematic and frequent micro-level data collection in developing economies to better understand the task content of occupations specific to each country as well as constraints and patterns of technology adoption at the firm level.

The remainder of this section presents the main shortcomings that limit a more detailed overview of the effects of technology adoption in low- and middle-income countries. First, we discuss the available measures of technology adoption (section 2.4.1) and tasks (section 2.4.2) and highlight the need for longitudinal and micro-level data. Following this discussion, we point out some of the main gaps in the (empirical) literature, focusing on those that could vastly improve our understanding and facilitate the development of appropriate public policies (section 2.4.3).

2.4.1 Measuring firm-level technology adoption

Emerging and developing economies lack information on technology adoption at disaggregated levels. Efforts to expand our knowledge in this direction would facilitate a finer understanding of the composition effects of technology adoption and expand our knowledge of the main barriers preventing the adoption of more advanced technologies among those economies. Some recent efforts have provided new evidence and data in this direction. For instance, a new survey by the World Bank offers granular information on the adoption (*extensive margin*) and use (*intensive margin*) of technologies for both general business functions and sector-specific business functions for several emerging and developing economies. Even though there is significant heterogeneity across firms, the results indicate that, on average, firms are adopting manual, pre-digital technologies (Cirera, Comin, Vargas Da Cruz, Lee, & Soares Martins Neto, 2021b). In addition, a novel database from UNIDO offers detailed information on the adoption of production technology in developing economies (see, for instance, Delera et al., 2022). The results also point to few firms adopting very advanced technologies and large heterogeneity among firms.

However, the continuous evolution of technologies (Dosi, 1982) makes it challenging to measure their adoption. Indeed, firms may need to maintain, upgrade or adapt the technologies embedded in their production processes over time - then, which of these decisions should be considered as technology adoption *per se*? The study of such dynamic systems, i.e. how technologies and their adoption evolve and how firms, workers and their skills coevolve, requires longitudinal data that allows tracking firms over time. Further data and research on this would allow improving our understanding of the relation between firm characteristics, local availability of skills, and technological paradigms in emerging and developing economies.

2.4.2 Measuring the task content of jobs across countries

Data collection and integration at a decentralized level with a detailed skill mapping system will help local economies to shape policies to foster skill upgrading and place themselves in a better position to respond to the threats and opportunities brought by technological change.

*Measuring tasks with the O*NET database*

The literature on RBTC explicitly explores differences in the task composition across occupations to study the labor market consequences of technological development. Within this approach, two main methods were developed, as also illustrated in column 4 of Table 2.2: the first one using the O*NET database, and the second one building on information about tasks from the PIAAC and/or STEP surveys (see also Table 2.2 for a general comparison of these measures). The first approach focuses on occupational level tasks, which provide information on job characteristics only at the occupational level but not at the worker level. Specifically, authors have used the Dictionary of Occupational Titles (DOT) survey and its updated version, the O*NET. Using the O*NET dataset, Autor et al. (2003) developed a "routine task intensity" index based on the routine, abstract, and manual task content for each occupation.[10] The use of the O*NET database allowed for a significant transition in the literature, as we are now able to measure the tasks performed in jobs rather than simply the educational level of workers performing them.[11]

This measure has been adopted also in the case of studies on developing countries, under the assumption that the task content across occupations is similar across countries.[12] However, the assumption that the task content of occupations is similar between countries is obviously a strong one. Differences in technology use are likely to result in different job tasks performed by a machine operator in the U.S. and those performed by a machine operator in a low-income country.

Measuring tasks with the PIAAC and STEP surveys

[10]The O*NET database covers nearly 1,000 occupations in the U.S. and provides occupational level task indexes estimated by experts, who rank occupations based on workers' interviews. Autor et al. (2003) selected a number of relevant variables for each of the five conceptual categories: non-routine analytic tasks, non-routine interactive tasks, routine cognitive tasks, routine manual tasks, and non-routine manual tasks. For instance, in measuring routine manual activity, the authors use the variable FINGDEX, an abbreviation of Finger Dextery.

[11]The literature on developed economies has also explored the survey of employees carried out by the German Federal Institute for Vocational Training (Bundesinstitut für Berufsbildung; BIBB) and the Research Institute of the Federal Employment Service (Institut für Arbeitsmarkt- und Berufsforschung; IAB) (see, for instance, Spitz-Oener, 2006, for additional details). However, the database only includes binary information on whether the worker either performs a specific task or not, and aggregate measures are based on the share of each category of tasks (abstract, routine and manual). In our review in section 2.2, authors have opted for using the O*NET database when studying job polarization in developing economies.

[12]For example, World Bank (2016) and Maloney and Molina (2019) follow Autor and Dorn (2013)'s classification and define 9 groups of occupations coded according to the major categories in the International Standard Classification of Occupations (ISCO) to study job polarization (see also Aedo et al., 2013 and Arias et al., 2014).

In response to this caveat, a second approach has used worker-level information provided by new household surveys such as the Program for International Assessment of Adult Competencies (PIAAC) by the Organisation for Economic Co-operation and Development (OECD) and the Skills Toward Employment and Productivity (STEP) by the World Bank. Both surveys attempt to measure tasks and skills across the developing world.[13]

Dicarlo et al. (2016) construct a measure of the skill content of occupations for ten low and middle-income countries using the STEP skill measurement surveys and compare it with that of the United States. A number of exciting facts result from this comparison: (i) first, along the skill dimension, occupations are ranked similarly across countries; (i) second, workers in higher-income countries use analytical and interpersonal skills more frequently; (iii) lastly, there are significant differences in the skill content across countries, so that assuming that the U.S. skill content is a good proxy for developing countries is wrong and likely to impact the estimates. Messina et al. (2016) also employ the STEP Surveys conducted in Bolivia and Colombia as a proxy for the routine/abstract/manual content of jobs in Latin America. They show that Latin American occupations exhibit a higher manual content than similar occupations in the United States. Similar results are discussed in Lo Bello et al. (2019), who apply the STEP survey for a more significant number of developing countries. The authors argue that indexes based on U.S. data do not provide a fair approximation of routine cognitive and non-routine manual skill content of jobs in developing countries. Lo Bello et al. (2019) also point out two caveats in using the STEP Surveys. First, as estimates are based on workers' responses, it is assumed that workers do not differ in their view of tasks performed at work. However, this assumption may not hold as most questions are subjective. Second, the survey focuses on urban areas, thus under-representing the agricultural sector.

[13] The use of direct worker-level information on the specific tasks performed on the job was pioneered by Handel (2008), who developed the STAMP survey.

Lewandowski et al. (2019) combine the STEP and PIAAC surveys and develop a harmonized measure of the task content of occupations based on Acemoglu and Autor (2011).[14] The authors find that workers in developed economies perform mostly non-routine cognitive analytical and non-routine cognitive interpersonal tasks. In contrast, workers in developing economies perform routine tasks more intensively. Moreover, Lewandowski et al. (2020) explore the PIAAC survey for several countries and develop a regression-based methodology to predict the country-specific routine task intensity of occupations, thus overcoming the lack of survey data for several large developing economies, such as Brazil and India. Besides corroborating that occupations in developing countries are more routine intensive, the authors also find that from 2000 to 2017, the gap in average routine-task intensity with respect to developed countries has increased. In contrast, Gasparini et al. (2021) use harmonized national household surveys for Latin America's six largest economies combined with task content based on information from the PIAAC surveys conducted in Chile, Mexico, Peru, and Ecuador. Applying the mean results derived from these four economies, the authors find a strong linear correlation between their measure of routine intensity and the routine task index developed by Autor and Dorn (2013). Finally, Caunedo et al. (2021) construct a measure of occupational task content using the PIAAC and STEP surveys from 2006 to 2015 and find that developed countries use non-routine analytical and interpersonal tasks more intensively than developing countries. In contrast, developing countries use routine cognitive and routine-manual tasks more intensively. In addition, the authors show that countries are converging to similar task intensities over this period.

Within-occupations variance

[14] Lewandowski et al. (2020) also present different task measures based on STEP and PIAAC data from other authors.

Another important aspect besides differences in task intensity across occupations is the extent of within-occupations variance in tasks. As discussed above, both DOT and O*NET provide information only at the level of occupations, not workers. Therefore, the implementation of worker-level surveys, including the PIAAC and STEP surveys discussed above, allow us to study within-occupations differences. For example, Autor and Handel (2013) explore data from the Princeton Data Improvement Initiative (PDII) survey (former STAMP) and document that tasks vary substantially within occupations in the U.S. Stinebrickner et al. (2019) take advantage of data from the Berea Panel Study and explore the contribution of task content to wage growth, finding that high-skilled tasks pay substantially more than low-skilled tasks. In the context of developing economies and to the best of our knowledge, Saltiel (2019) is the only paper to consider the returns to worker-level task measures. The author explores work-level data from the STEP survey for 10 low- and middle-income countries, finding substantial variance in task intensity within occupations and suggesting that non-routine analytic and interpersonal tasks are associated with sizable wage premiums. In addition, the empirical findings suggest that more educated workers sort into occupations with higher non-routine task content.

Evolution of tasks over time

Despite the recent developments in task measurement across the developing world, the literature still lacks information on the evolution of tasks. Not only do occupations differ across countries, but they also evolve over time. For instance, using data from job ads from the Boston Globe, the New York Times, and The Wall Street Journal, Atalay et al. (2020) demonstrate that words related to routine tasks have declined in frequency over the period from 1950 to 2000 in the U.S. Furthermore, Garcia-Couto (2020) harmonizes data from three different rounds of the Dictionary of Occupation Title (DOT) and the Occupational Information Network (O*NET) and finds that the cognitive intensity of occupations has increased during the last decades and that a significant share of changes in wages is due to increases in the return and the intensity of cognitive tasks. Similar trends are also observed by Cassidy (2017) and Spitz-Oener (2006), who use the German Qualification and Career Survey conducted by Federal Institute for Vocational Education and Training (BIBB) and the Institute for Employment (IAB).

As for developing economies, it remains unclear whether (and to what extent) changes in tasks within occupations are similar to what we observe in advanced economies. Most analyses still rely on occupational and sector composition information to determine the extent of polarization without a clear understanding of changes in task requirements over time. An obvious reason for this gap is the lack of longitudinal data sources, which subsequent rounds of the STEP and PIAAC surveys could overcome. Thus, in addition to expanding the number of countries covered in the study, especially emerging economies, it is also critical to gather information on worker-level tasks within countries over time. Another way forward would be to use job ads from job platforms to study the demand for digital skills and non-routine tasks in developing countries. Following the methodology proposed by Atalay et al. (2020), researchers could explore other platforms to study the evolution of tasks demanded in some emerging economies. Yet, researchers should also be aware of some issues in using job ads data, particularly that they under-represent certain sectors and occupations, for instance, the construction sector and occupations related to the production and transportation of goods. In addition, these job ads might not capture jobs from the informal sector, which represents a significant share of the workforce in developing and emerging economies.[15]

[15] Note, however, that some statistical offices from these countries make an important effort to record informal work and related occupations. For instance, Firpo et al. (2021) explores Brazil's formal and informal sectors when discussing job polarization.

Table 2.2: Comparing the different measures of tasks

	O*NET	STEP	PIAAC
Countries	United States	Albania, Armenia, Azerbaijan, Bolivia, Bosnia & Herzegovina, Colombia, Georgia, Ghana, Kenya, Kosovo, Lao PDR, Macedonia, Serbia, Sri Lanka, Ukraine, Vietnam, and the Yunnan Province in China. The third wave of the China Urban Labor Survey (CULS) includes a section based on the STEP survey. It includes information on Guangzhou, Shanghai, and Fuzhou on the coast, Shenyang in the northeast, Xian in the northwest, and Wuhan in central China	Australia, Austria, Belgium (Flanders), Canada, Chile, Czech Republic, Denmark, Ecuador, Estonia, Finland, France, Germany, Greece, Hungary, Indonesia, Ireland, Israel, Italy, Japan, Kazakhstan, Korea, Latvia, Lithuania, Mexico, Netherlands, New Zealand, Norway, Peru, Poland, Russian Federation, Singapore, Slovak Republic, Slovenia, Spain, Sweden, Turkey, United Kingdom (England and Northern Ireland), and the United States
Measure	Composite measures of O*NET work activities and work context importance scales. For each occupation, experts assign a score—between 1 and 5 to the 44 existing tasks	Workers are asked about specific tasks. STEP questions typically refer to whether workers perform a specific task as part of their job or not	Workers are asked about specific tasks. Often, the PIAAC questions refer to the frequency of performing a task (five categories ranging from "never" to "every day")
Caveats	• Assumption that the task content of occupations is similar across countries and constant over time • Includes "numerous potential task scales, and it is rarely obvious which measure (if any) best represents a given task construct" (Acemoglu & Autor, 2011, p.1078) • No variation in the task scores within occupations	• Only covers urban areas; • Does not cover large developing economies, including, for instance, Argentina, Brazil, Bangladesh, India, Nigeria, and South Africa • The mapping between tasks and skills is not trivial • Subject bias in workers' response, especially given that most questions are subjective • Sample size is not large enough to develop disaggregated classifications at the country level	• Does not cover large developing economies, including, for instance, Argentina, Brazil, Bangladesh, India, Nigeria, and South Africa; • The mapping between tasks and skills is not trivial • Subject bias in workers' response, especially given that most questions are subjective • Sample size is not large enough to develop disaggregated classifications at the country level
Advantages	• Offers task content of occupations at disaggregated levels and with easily-available crosswalks to most classifications	• Variation in the task scores within occupations; • Estimation for a number of developing countries, including low-income economies	• Variation in the task scores within occupations; • Estimation for a number of developing countries

Source: Own elaboration. STEP and PIAAC also present differences in the way the data is collected and in the way the proficiency of respondents is estimated (see Keslair & Paccagnella, 2020).

2.4.3 Future research directions

As discussed in section 2.3, there is little evidence of the underlying mechanisms explaining the slow polarization pace in low- and middle-income countries. Geographical, sectoral, and firm heterogeneities have largely been overlooked, as most studies have focused on aggregate measures. In many cases, the lack of research stems from appropriate information. In this context, firm-level details on the adoption of more advanced technologies and longitudinal measures of tasks as described above will enable a significant leap in the literature.

In addition, tracking workers' transitions across occupations and in and out of unemployment could improve public policies and help design or improve a safety net minimizing the harms of technological change. For instance, the literature has not explored the extent to which the declining demand for routine occupations takes place within worker categories or through changes in the composition of workers. If workers can easily transition between routine and non-routine occupations, technological unemployment becomes less of an issue.

Public policies can play a crucial role if job polarization occurs through workers' composition changes. For instance, Cortes et al. (2020) show that most of the decline in routine occupations in the U.S. is linked to the inflow rates to routine employment (from unemployment and non-participation, i.e. less workers starting a routine job) rather than the outflow rates (more routine workers losing their job). Moreover, Maczulskij (2019) explores Finnish data and shows that most of the relative increase in non-routine occupations compared to mid-level routine occupations is a within-worker phenomenon in the decomposition analysis. In contrast, the share of low-skilled non-routine manual tasks has increased mainly through entry dynamics.

Additionally, we need a more detailed analysis of the effects of labor-displacing automation on workers' labor prospects, especially in the context of increasing digitalization. One crucial empirical question concerns which types of workers have a more pronounced decline in wages and increase in unemployment duration following the event of displacement. Despite the long-term drop in demand for routine tasks, little is known about the short-term impacts of technological change at the individual level, and less so in the context of developing countries. Although most empirical results point to a lack of polarization among those economies, it is still unclear whether workers previously employed in routine-intensive occupations are already facing the negative implications of automation.

In the context of advanced economies, a number of studies show that automation increases the probability of incumbent workers separating from their employers (Bessen et al., 2019), and that displaced workers in routine-intensive occupations are more likely to face long-term unemployment and a decrease in wages and number of days worked (Bessen et al., 2019; Blien et al., 2021; Goos et al., 2021). However, the literature on developing economies is much thinner. Expect for Martins-Neto et al. (2022), who finds that displaced individuals in routine-intensive occupations face longer unemployment rates in Brazil, no other study has sought to investigate the implications of routinization at the individual level in the context of developing countries. A detailed account of the effects of displacement on different kinds of workers could help in assessing the differential impacts on employment and income distribution. This in turn will help to categorize more disadvantaged workers, thereby formulating specific policies for various categories (including unemployment benefits).

Therefore, while the literature on job polarization in developing countries is relatively new, the research agenda should concentrate on understanding the factors behind the slow pace of job polarization and examining the heterogeneities of this process, especially those related to firm-level differences in technology adoption and the adverse impacts at the worker level. As discussed in this section, researchers could expand our understanding of the many heterogeneities surrounding labor market trends in emerging economies while exploring matched employer-employee databases.[16]

Two other dimensions that require further research are the roles of the type of technology and the way technology adoption affects firms' internal organization. First, employment dynamics depend on the nature of technologies, i.e., which skills they complement or substitute. This has been the focus of several recent works highlighting the new patterns linking digital technologies and demand for skills in advanced economies (Acemoglu & Restrepo, 2020; Frey & Osborne, 2017). However, such a relationship is also mediated by firms' own organizational routines and adaptations, which affect how technologies remodel production and workers' tasks within firms (Ciarli et al., 2021; Dosi & Nelson, 2010; Dosi & Virgillito, 2019). Firms intentionally invest in organizational arrangements, practices, and routines to create new business models in response to the changing and increasingly complex technological landscape (Colfer & Baldwin, 2016). The employment effects of technology in developing and emerging economies could therefore be significantly related to the complex interplay between technologies, innovation, and skills driven by organizational restructuring, highlighting the need for urgent attention and more research in this area.

2.5 Conclusions

While studying the impact of technological change on jobs and how it affects economies and societies, one must recognize the existing differences among countries that emerge from different socioeconomic systems, levels and distributions of income, institutional contexts, and industrial structures. The nature and long-term impact of technologies created and adopted in different economies very much relate to the existing institutional and political contexts.

[16]Such data is available in several developing economies, including Brazil, Mexico, South Africa, Morocco, and Tunisia.

In this review, we have highlighted the impacts of technology adoption on the labor market, focusing on the extent of job polarization in developing and emerging economies. The evidence synthesis suggests that, in advanced economies, the rapid spread of ICTs and robots has resulted in increasing inequality and the "hollowing out" of the occupational distribution, with a significant decline in the demand for routine occupations (Acemoglu & Autor, 2011; Spitz-Oener, 2006). Yet, in economies at lower levels of income per capita, the pace is considerably slower, with little evidence of labor market polarization or labor-displacing automation (Firpo et al., 2021; Gasparini et al., 2021; Maloney & Molina, 2019).

In section section 2.3, we explored the possible mechanisms slowing job polarization in developing economies, suggesting the critical role of firms' and workers' capabilities in slowing technology adoption and the off-shoring of routine-intensive jobs from advanced economies to some host developing countries. Other moderating aspects include lower wages and different economic structures in emerging economies. We also highlighted the need for more research on the moderating sources, especially those associated with differences in the relative cost of inputs (lower wages in developing countries) and the role of MNEs in slowing or spurring job polarization.

Finally, in section 2.4, we have stressed the need for micro-level studies and the exploration of the different mechanisms preventing job polarization in those economies. These studies would enhance our understanding of the main barriers to technology adoption and the adverse effects at the worker level, thus allowing for the development and implementation of better-adapted policies fitted to developing and emerging economies' specific contexts.

3

Routine-biased Technological Change and Employee Outcomes after Mass Layoffs: Evidence from Brazil

This chapter is based on Martins-Neto, A., X. Cirera, A. Coad, Routine-biased technological change and employee outcomes after mass layoffs: Evidence from Brazil. *Industrial and Corporate Change*, forthcoming.

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 task intensity; Job displacement; Mass layoffs; Occupational mobility; Brazil

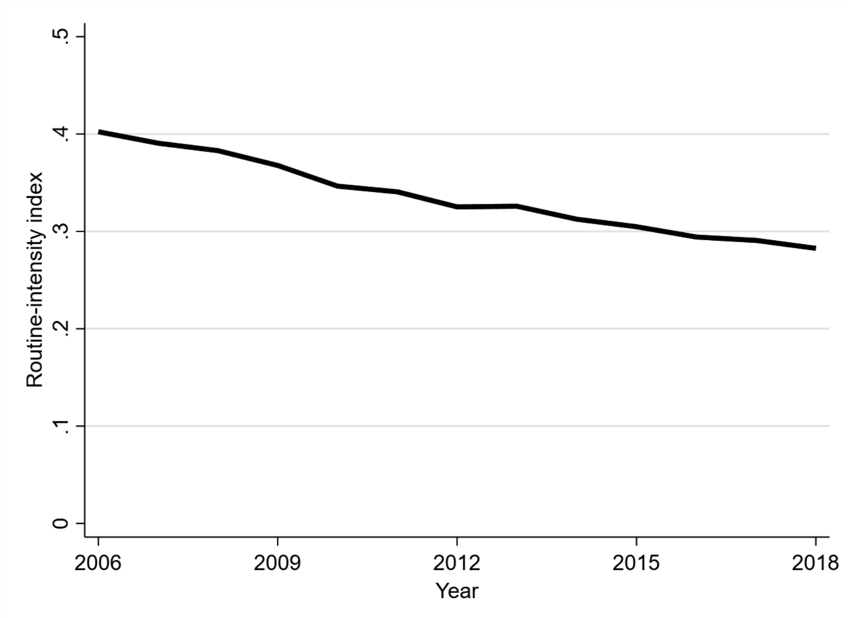
3.1 Introduction

Creative destruction has been referred to as the engine of modern economic growth (Aghion et al., 2021; Aghion & Howitt, 1992; Romer, 1990; Schumpeter, 1942) and a key driver of productivity differences across countries (Comin & Hobijn, 2010; Comin & Mestieri, 2018; Easterly & 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. Technological change has profound effects on labour markets (Barbieri et al., 2019; Piva & Vivarelli, 2018; Van Roy et al., 2018), and furthermore these effects are not homogenous. 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 usually concentrates among middle-earning workers (Acemoglu & 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 & 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). The picture is less clear in developing economies, however, where indications of job polarization are considerably weaker.[1]

[1] Maloney and Molina (2019) and Das and Hilgenstock (2022) find little evidence of labor market polarization or increased inequality in developing countries, either in absolute employment levels or workforce share. Gasparini et al. (2021) find similar results for Latin America's six largest economies, showing no evidence for polarization in the labor market. Martins-Neto et al. (2021) offer a literature review

Figure 3.1: Evolution of routine task intensity in Brazil



Source: Own elaboration. The routine task intensity (RTI) index is based on Goos et al. (2014) and measures the relative importance of routine tasks among all tasks associated with a given occupation. 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 task 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

of job polarization in developing economies.

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 task intensity of occupations declined considerably. Figure 3.1 highlights this result, displaying the decline of routine tasks in Brazil from 2006 to 2018.

Regardless of polarization, 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 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 helps fill this gap.

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 & Placzek, 2010; Jacobson et al., 1993; Raposo et al., 2019), treating mass layoffs as an exogenous 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 task intensity.

We contribute 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%-25% depending on the region and methodology.[2] Using Brazil's matched employer-employee data set (RAIS) in the mid-1990s, Menezes-Filho (2004) finds that high-tenure workers suffer a long-term loss in monthly wages of about 20% per year. Saltiel (2018) found similar results for Brazilian labor market outcomes over 2002-2012: 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 Lachowska et al. (2020), Fallick et al. (2021), and Bertheau et al. (2022), we estimate the loss of employer-specific wage premia.

We also contribute to the recent literature in labor economics that investigates 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.[3] They find that automation at the firms increases workers' separation risk, and that displaced workers are more likely to work fewer days in subsequent years. However, unlike our analysis, they 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 automotive plant. After the plant closed, and in line with RBTC, workers in routine-intensive occupations were less likely to find a job 1.5 years later. Additionally, for those workers who found a job, the non-routine content of job tasks was higher, wages were lower, and permanent jobs were less frequent. In line with

[2] See e.g. 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), and Raposo et al. (2019).

[3] See also Domini et al. (2021, 2022a).

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, they focus on a case study of one firm, which raises questions about possible selection bias, endogeneity, and generalizability of the results. Closest to our paper is Blien et al. (2021)'s analysis of German displaced workers (1980-2010), which tests 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 increased over time.

An important contribution of this study is to examine the impact of RBTC in the context of a middle-income country (i.e. 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 labor market frictions and mismatches. For instance, hiring costs and firms' entry costs in the form of taxes and bureaucracy burden are large in Brazil (Ulyssea, 2010), such that workers are more likely to bear the brunt of adjustment costs associated with shocks (Hollweg et al., 2014). 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 weak technological change. Fourth, in many developed economies, participation in GVCs spurred "routinization". However, Brazil 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 an interesting case study to explore "routinization."

An additional contribution is the heterogeneity analysis, including differences by gender, tenure, 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.

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, there is 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. We also find that the loss of employer-specific wage premiums explains 13% of the decline in wages for the treated group. We then 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, heterogeneity analysis suggests 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, 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 premia does not explain routine-intensive workers' more substantial reduction in wages.

The paper is structured as follows. Section 2 describes the data sources and defines 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. Section 6 concludes.

3.2 Data and sample construction

3.2.1 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 40 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 map information from the O*NET database to the CBO. Despite the increased availability of surveys collecting information on tasks performed by individual workers, including the Program for International Assessment of Adult Competencies (PIAAC) by the Organisation for Economic Co-operation and Development (OECD) and the Skills Toward Employment and Productivity (STEP) by the World Bank, information is not available for the case of Brazil. Therefore, to explore routine task intensity in developing economies, many authors have opted to use the O*NET database, assuming that the task content across occupations is similar across countries (e.g., Aedo et al., 2013; Arias et al., 2014; Maloney & Molina, 2019; World Bank, 2016).

Nevertheless, recent research has indicated that the task content may differ across countries and is notably correlated with income per capita (Lewandowski et al., 2019). For a given occupation, workers in high-income countries perform fewer routine tasks than those in poorer economies. Although we agree that country-specific measures of routine task intensity would improve the estimates, using O* NET is a reasonable approximation for Brazil for two main reasons. First, the central assumption in our paper is that the ranking of occupations in terms of routine task intensity may not vary significantly across countries. In other words, if technology adoption reduces the routine content of occupations, we assume that it equally affects all occupations, resulting in a similar ranking across countries - a manager will perform fewer routine tasks than an office clerk, irrespective of the country. This assumption is empirically confirmed by Dicarlo et al. (2016), who indicates that rankings of occupations along the skill dimensions are quite stable across countries. Moreover, Brazil is an upper-middle-income country. As a result, differences in routine task intensity for a given occupation would not be as significant.

Therefore, we follow Goos et al. (2014), who mapped the routine task intensity index (RTI) to ISCO-88 occupations. The 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.[4] The 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. We map these occupations to the Brazilian Code of Occupations. Table 3.1 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).

[4]Specifically, Manual tasks relate to the occupation's demand for "eye-hand-foot coordination" (EYEHAND), 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.

Table 3.1: 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).

3.2.2 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.[5]

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

[5] 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.

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 for those workers with multiple full-time employment. 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-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 & 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)).[6] By including workers' wage growth, we

[6]We have not to imposed any bins in our matching strategy and have used the bin-

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 3.2 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 treatment 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 3.12 shows the histogram of the routine-intensity index for the matched sample).

ning algorithm autocuts proposed in the CEM command in Stata.

Table 3.2: 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	—	—

Note: 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. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

3.3 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 & 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:

$$y_{it} = \alpha_0 + \sum_{k=-3,k\neq-2}^{5} [\nu_t^k + \nu_t^k T_i \beta_k] + \lambda_i + \theta_t + \delta_s + \sigma_j + \epsilon_{ijst} \tag{3.1}$$

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 3.1 such that:

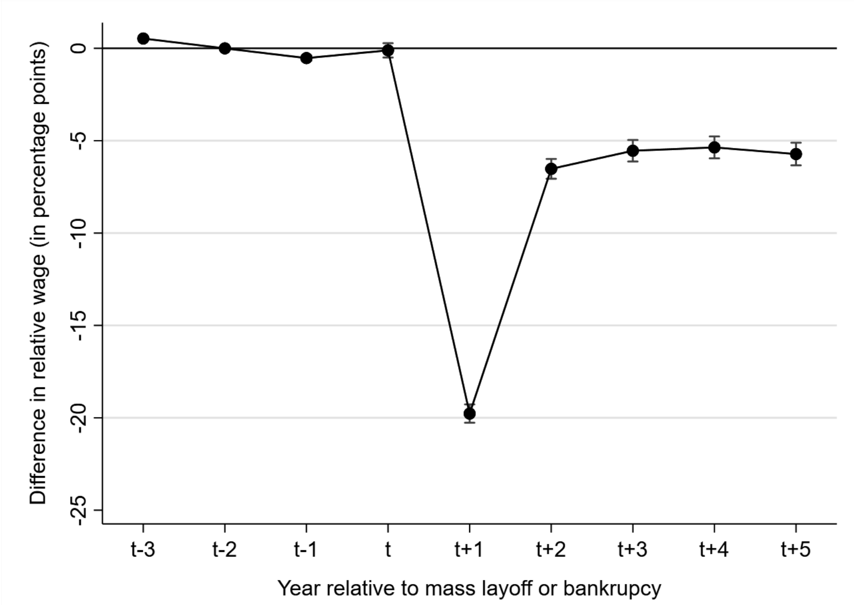
$$y_{it} = \alpha_0 + \sum_{k=-3,k\neq-2}^{5} [\nu_t^k + \nu_t^k T_i \beta_k + \nu_t^k RTI_i \alpha_k + \nu_t^k T_i RTI_i \rho_k] + \lambda_i + \theta_t + \delta_s + \sigma_j + \epsilon_{ijst} \tag{3.2}$$

where RTI_i is the routine task intensity index described in Table 3.1. In addition to worker fixed effects, time-to-event dummies, and regular year, region, and sector dummies, Equation 3.2 also includes interactions between time-to-event dummies and routine task intensity ($\alpha_k \nu_t^k RTI_i$) and the triple interaction between routine task 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 task 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 task intensity index. The latter is our main outcome of interest.

3.4 The adverse effects of job displacement

We start by first exploring the impact of job displacement on wages and employment in Brazil. Figure 3.2 plots the coefficients from Equation 3.1 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 in 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.

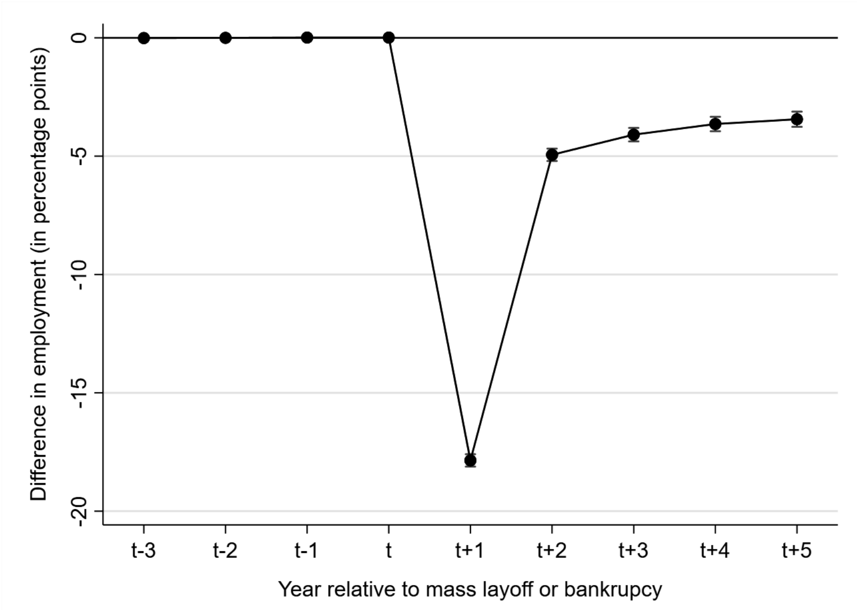
Figure 3.2: Effect of displacement on relative wages



Note: 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 the individual level.

Figure 3.3 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 3.9 in the Appendix presents the coefficients for each year).

Figure 3.3: Effect of displacement on employment



Note: 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 the 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 3.3 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 3.3: Effect of displacement on relative wages and employment by group

	Relative wages		Relative employment		
	Mean effect	*Stand. Errors*	*Mean effect*	*Stand. Errors*	*Observations*
Age					
31 years or younger	-0.0744***	(0.00386)	-0.0510***	(0.00182)	697,329
32 to 41 years	-0.0717***	(0.00272)	-0.0542***	(0.00140)	1,133,379
42 years or older	-0.0682***	(0.00339)	-0.0667***	(0.00199)	606,050
Tenure					
48 months or less	-0.0642***	(0.00367)	-0.0501***	(0.00185)	708,183
49 to 84 months	-0.0675***	(0.00284)	-0.0495***	(0.00147)	1,065,123
85 months or more	-0.0871***	(0.00346)	-0.0741***	(0.00179)	663,452
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

Note: 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 the individual level are reported in parentheses. ***, **, and * respectively indicate 0.01, 0.05, and 0.1 levels of significance.

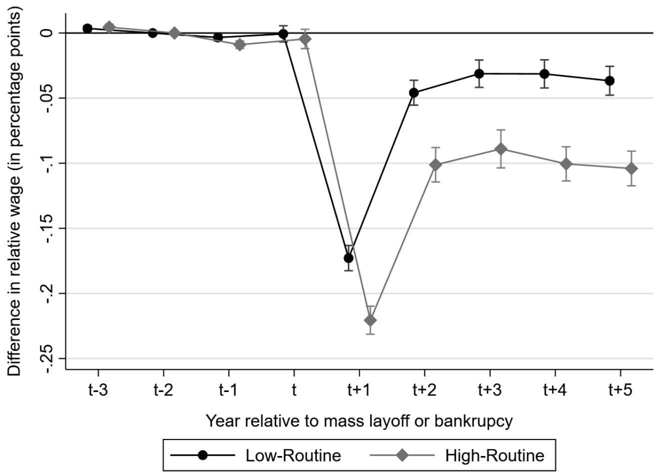
Several interesting facts emerge. First, in terms of employment, and consistent with the literature (Deelen et al., 2018), the adverse effects are more significant for older workers. 42 years or older workers face a decline in employment about 1.5 percentage points larger than younger individuals. In 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 85 months of experience in the same firm see their wages declining on average 8.7% 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 (7.4%) than short-tenured workers (5%). We also find that male workers are less impacted than female individuals in terms of relative wages and employment. The results are different from 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.

3.5 routine task intensity and the cost of displacement

3.5.1 The role of tasks

Mass layoffs are a natural experiment to explore the role of routine task 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 task 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 & 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 & Siegel, 2018).

Figure 3.4: Effect of displacement on relative wages by occupational group

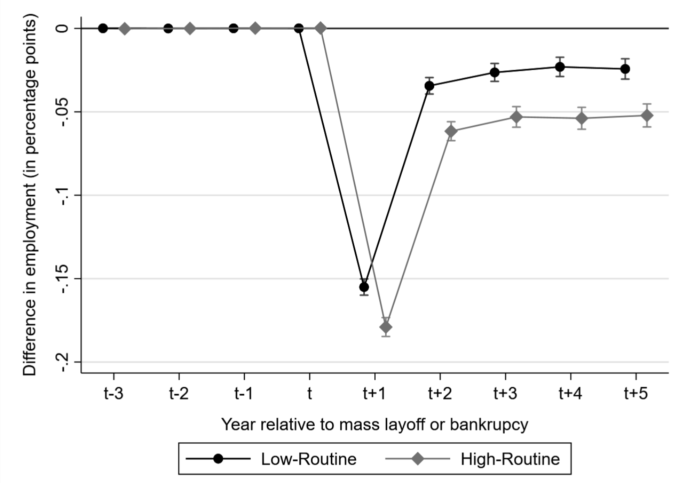


Note: The figure shows the estimates of time-to-event dummies interacted with a displacement indicator from a regression including individual, region, sector, time-to-event dummies, and year fixed effects. The dependent variables is relative wages. Relative wages is measured dividing worker's monthly 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 the individual level.

Figure 3.4 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 3.1, 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 3.10 shows the results of a similar exercise than in Table 3.3, and reinforces the fact that workers in high-routine occupations are more impacted in terms of wages. In addition, Figure 3.5 shows that workers in the fourth quartile are 2% more likely to face unemployment in the years following the shock.

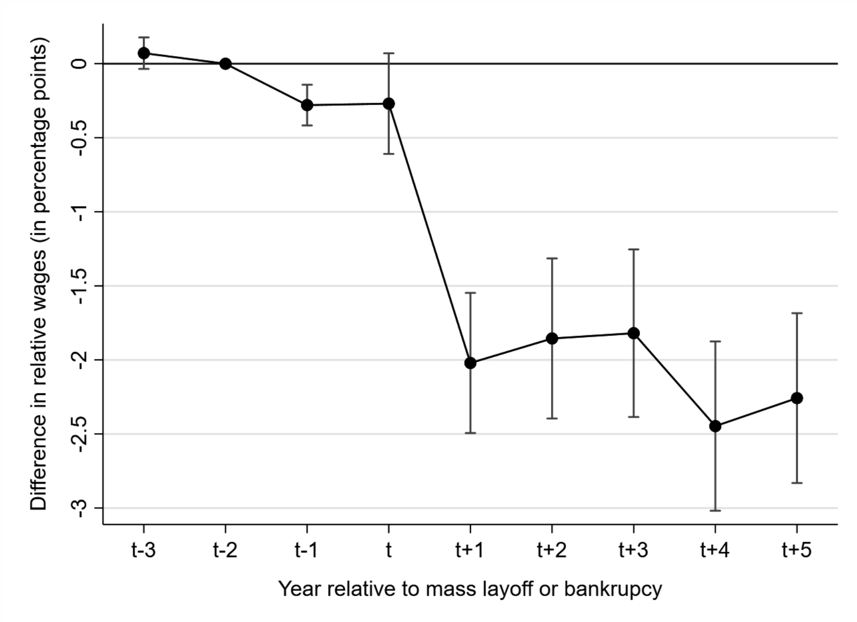
Figure 3.5: Effect of displacement on employment by occupational group



Note: 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 the 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 3.6, which offers the estimates from Equation 3.2 and presents the coefficient of the triple interaction term (ρ_k) taking relative wages as the dependent variable. Table 3.13 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 task intensity index, which in turn varies from -1.52 to 2.24.

Figure 3.6: Routine task intensity and the effect of displacement on relative wages

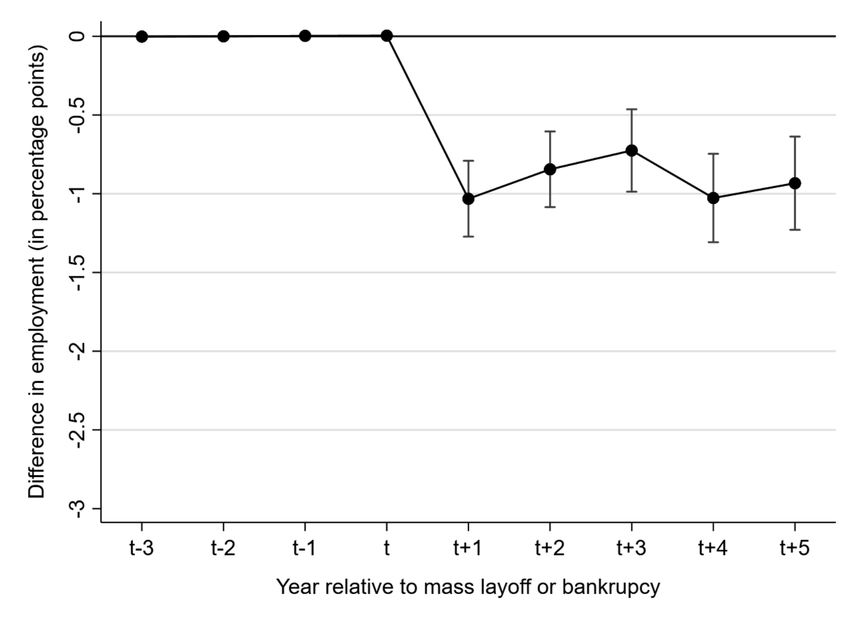


Note: The figure shows the estimates of the triple interactions between time-to-event dummies interacted with a displacement indicator and a routine task intensity measure from a regression including individual, region, sector, time-to-event dummies, time-to-event dummies interacted with the routine task 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 the individual level.

The results suggest that an increase of 1 point in the RTI results in a further decline of about 2% in 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 3.7 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.[7]

[7] Regarding the more significant adverse effect of displacement for workers in high routine occupations, Table 3.11 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 3.7: Routine task intensity and the effect of displacement on employment



Note: The figure shows the estimates of the triple interactions between time-to-event dummies interacted with a displacement indicator and a routine task intensity measure from a regression including individual, region, sector, time-to-event dummies, time-to-event dummies interacted with the routine task 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 the individual level.

Keeping our focus on job displacement and routine task intensity, we investigate the robustness of our findings according to heterogeneity in individuals' characteristics.[8] Table 3.4 examines the heterogeneity

[8]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

of these findings, as in Table 3.3, while estimating Equation 3.2. 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, considering differences across sectors, the role of job switchers, and firm heterogeneity.

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.

workers' characteristics is beyond the scope of the current paper, further work on different samples would be welcome.

Table 3.4: Effect of routine task intensity on relative wages and employment by group

	Relative wages		**Relative employment**		
	Mean effect	*Stand. Errors*	*Mean effect*	*Stand. Errors*	*Observations*
Age					
31years or younger	-0.0102***	(0.00368)	-0.00430***	(0.00167)	680,508
32 to 41 years	-0.0182***	(0.00266)	-0.00869***	(0.00130))	1,099,836
42 years or older	-0.0241***	(0.00333)	-0.0129***	(0.00188)	584,099
Tenure					
48 months or less	-0.00903***	(0.00358)	-0.00261***	(0.00172)	687,816
49 to 84 months	-0.0185***	(0.00275)	-0.00901***	(0.00136)	1,034,622
85 months or more	-0.0228***	(0.00334)	-0.0102***	(0.00162)	642,005
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

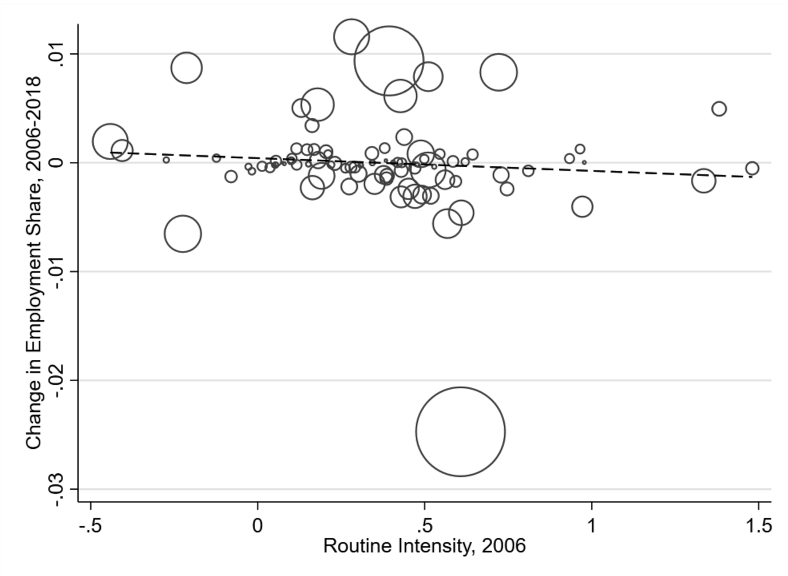
Note: The table shows averages of the estimates over the 6 years from the shock (from t to $t+5$) of the triple interactions between time-to-event dummies interacted with a displacement indicator and a routine task intensity measure from a regression including individual, region, sector, time-to-event dummies, time-to-event dummies interacted with the routine task 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 by dividing workers' monthly average wage by the 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 the individual level are reported in parentheses. ***, **, and * respectively indicate 0.01, 0.05, and 0.1 levels of significance.

3.5.2 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; Lyshol, 2022). 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 3.1 shows a constant decline in routine task 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 task intensity differs across sectors, such that sectoral employment shifts also explain aggregate occupational share changes (Goos et al., 2014).

Figure 3.8: routine task intensity and Change in Industries' Employment Share



Note: Circles represent 87 sectors, weighted by total employment in 2006. The x-axis is the RTI index, calculated as the weighted occupational index and ranging from -1.52 to 2.24. 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 task intensity across sectors and the change in employment share from 2006 to 2018. Figure 3.8 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:

$$\Delta RTI = \sum_i \Delta RTI_i S_{i0} + \sum_i RTI_{i0} \Delta S_i + \sum_i \Delta RTI_i \Delta S_i \qquad (3.3)$$

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 3.5 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 3.9 presents the change in routine task intensity across sector over the period. (Table 3.14 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

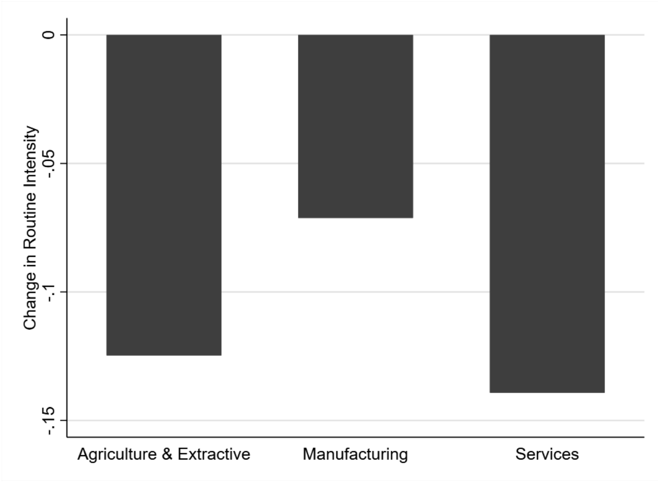
Table 3.5: RTI decomposition, 2006-2018

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

Note: 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.

research relates the decline in routine tasks to automation in manufacturing, the services industry presents a more significant decrease in routine task intensity in Brazil. In particular, the decline in routine task 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 3.9: Change in Sectors' routine task intensity



Note: 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 3.2. 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 3.6 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 3.6: 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

Note: 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. Rows (1) and (2) split the 87 sectors between non-manufacturing and manufacturing. Rows (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.

3.5.3 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 3.12 for a descriptive analysis of switchers and non-switchers). Columns (1)-(2) in Table 3.7 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 3.7: 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	262,716	262,714	262,716	262,711

Note: 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 3.7 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 3.2. Column (1) in Table 3.8 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 3.8: 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	446,886	1,917,558
R-squared	0.374	0.374

Note: 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.

3.5.4 Firms fixed effects

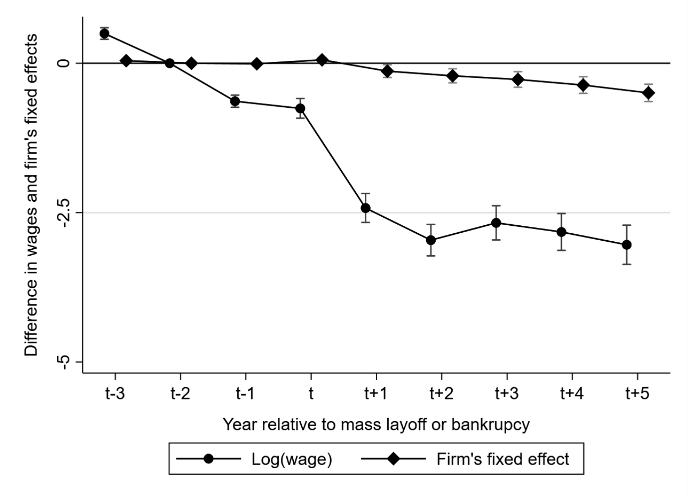
A third and related mechanism to explain worse employment outcomes for routine occupations is that workers in high routine intensive occupations have to move to low-paying and worse companies to find a job in the same field. For instance, less productive firms tend to have lower adoption of more sophisticated 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.[9]

With firms fixed effects in hand, we estimate Equation 3.1 using the fixed effects as the outcome variable and compare with the impacts on workers' logarithm of monthly wages. Figure 3.10 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.

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

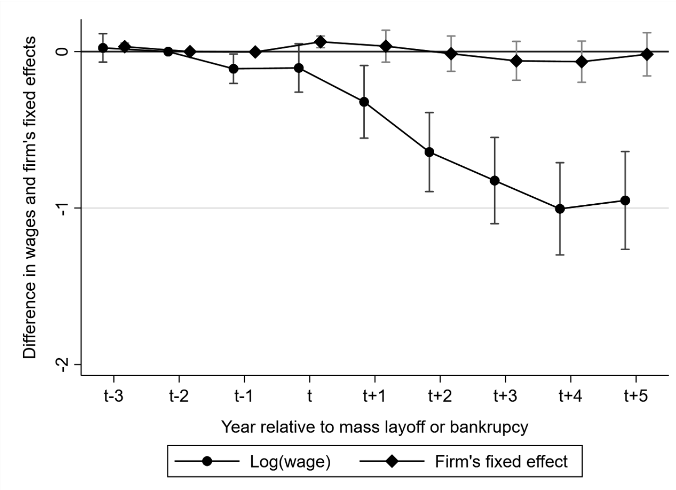
Figure 3.10: Job displacement and the loss of employer-specific wage premium



Note: 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 3.2 to test whether the RTI is associated with movements to low-paying firms. On the one hand, Figure 3.11 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 3.11 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 3.11: Effect of displacement on employment by occupational group



Note: The figure shows the estimates of the triple interactions between time-to-event dummies interacted with a displacement indicator and a routine task intensity measure from a regression including individual, region, sector, time-to-event dummies, time-to-event dummies interacted with the routine task 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.

3.6 Conclusion

Technological change puts pressure on certain worker groups by eroding the value of their skills, threatening their job security, and making it harder to find jobs with equivalent pay after a layoff (Braxton & Taska, 2023). While these phenomena have been widely studied in the US and Europe, much less is known about the potential impact on employment dynamics in developing countries, where the pace is technological change is slower. This paper sheds some light on this issue for a large middle-income country, Brazil, by understanding the employment dynamics associated with routine workers and using mass layoffs as a natural experiment to better identify these effects.

In line with other evidence in developed countries, we find that job displacement has a significant impact on workers' labor outcomes. 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. 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, long-tenured, and older workers are more significantly affected by displacement.

But while all workers experience a significant decline in wages and employment opportunities following a mass layoff event, those in routine intensive occupations fare much worse – especially less-educated workers. 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, while we do not find evidence of a necessary move towards "worse" firms by displaced workers, those in routine occupations are also more likely to have to switch occupations.

Several policy implications arise from these findings. First, while policies that effectively accelerate technological change have large potential returns in terms of productivity growth in developing countries, the findings of this paper identify potential negative distributional impacts on routine workers in middle-income countries as technological change accelerates. Second, workers in routine-intensive occupations appear especially vulnerable after a mass layoff because of the significant wage decrease and the difficulty of finding a new job requiring similar skills. Thus, policies aimed to re-skill the labor force are not only necessary, but they need to prioritize workers in routine-intensive occupations and sectors with a larger decrease in demand for routine-intensive occupations, supporting them in developing new skills that can help offset the harmful impacts of displacement. In addition, a more nuanced understanding of the tasks these groups perform is needed, especially of the need for soft skills that can also facilitate job transitions. As the pace of technological change and automation shows no sign of slowing down, policy interventions for training and re-skilling displaced workers can only be expected to grow in importance, also in developing countries.

Some important gaps in understanding the impact of technological change on workers' dynamics in developing countries still remain. More granular evidence is needed linking direct events of technology upgrading with changes in the skill composition at the firm and workers' levels. Rather than inferring technological trends based on the changes in occupation skills demand within sectors, more detailed data is needed to identify how specific technologies affect the employment outcomes of different types of workers. This requires more availability of surveys that measure technology use in establishments, and that can be linked with large labor censuses and other administrative data.

3.7 Appendix

Figure 3.12: Histogram routine-intensity index

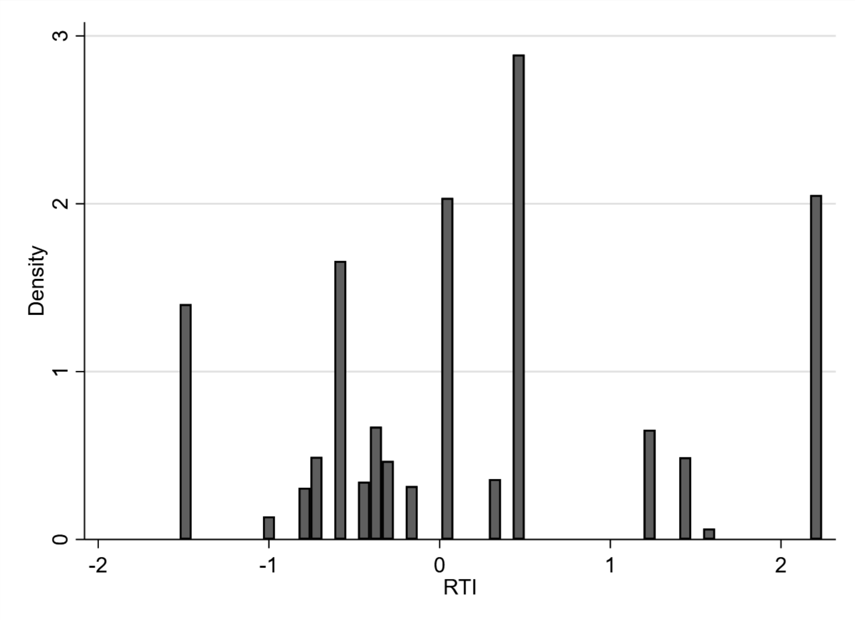


Table 3.9: Effect of displacement on wages and employment

	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

Note: 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 3.10: 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

Note: 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 by dividing workers' monthly average wage by the 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 the individual level are reported in parentheses. ***, **, and * respectively indicate 0.01, 0.05, and 0.1 levels of significance.

Table 3.11: 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	—

Note: 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 3.12: 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	—	—

Note: 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 3.13: 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

Note: 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 3.14: 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
[illegible]	[illegible]	[illegible]	[illegible]

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		

4

Forced Displacement and Occupational Mobility: a Skills-based Approach

This chapter is co-authored with Renata Mayer Gukovas and Didier Fouarge.

Abstract

We focus on mobile workers because of forced displacement and study how their occupational skills match to skills in other occupations, and how this commonality of skills relate 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 1.2% 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

4.1 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 & Dorn, 2013; Braxton & 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.

[1]For example, there is accumulating evidence that workers are more likely to switch to occupations with similar tasks (Gathmann & Schönberg, 2010; Poletaev & 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, 2022), and unemployment exits to more distant occupations are associated with lower re-employment wages (Lyshol, 2022; Nedelkoska et al., 2015).

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 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

[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 & Placzek, 2010; Eliason & 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., 2019). 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 & Steffes, 2010)[3], and skills transferability and the loss of occupational-specific knowledge (Becker, 1962; Gathmann & Schönberg, 2010).

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 & 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' 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 2.8% 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.

4.2 Data

4.2.1 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

[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.

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.

4.2.2 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., 2019) and define mass layoffs when 30% 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 4.1 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 (see section 5.6 for additional descriptions by state). 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 4.1: 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.

4.2.3 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, 2022; 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]

[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,

4.2.4 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:

$$JSI_{ij} = \frac{HC_i \cap HC_j}{HC_i \cup HC_j} \tag{4.1}$$

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 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.

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.

[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

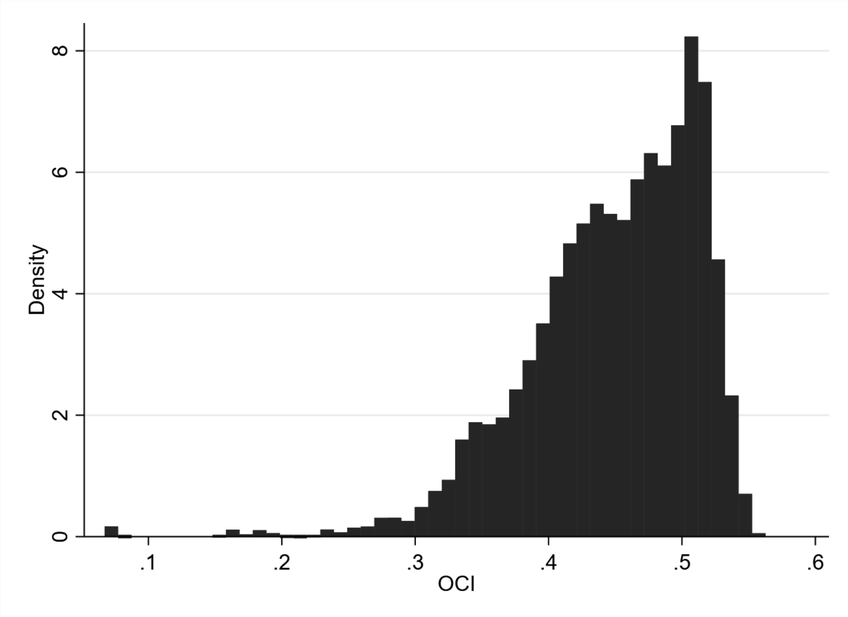
While the JSI gives the distance between each pair of occupations, we want to observe the worker's position concerning all other occupations in the market in which they supply their labor. For this purpose, and similar to Eggenberger et al. (2022), we calculate the average distance of the worker's occupation 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):

$$OCI_{imt} = \sum_{j=1}^{N} JSI_{ij} \frac{L_{jmt}}{L_m t} \tag{4.2}$$

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 4.1 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 4.2 indicates that models and telemarketers are among the most specific occupations. At the same time, construction supervisors and packaging and labeling workers supervisors are the occupations with the largest OCI.

[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.

Figure 4.1: Distribution of the OCI



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

Table 4.2: 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

4.3 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 apply a two-way fixed effects regression as follows:

$$y_{it} = \lambda_i + \sum_{k=-3,k\neq-2}^{5} [\nu_t^k \beta_k + \nu_t^k OCI\theta_k] + \delta_s + \sigma_j + \epsilon_{ijst} \tag{4.3}$$

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:

$$log(wage) = \lambda_i + \sum_{k=-3,k\neq-2}^{5} [\nu_t^k \beta_k + \nu_t^k JSI\theta_k] + \delta_s + \sigma_j + \epsilon_{ijst} \quad (4.4)$$

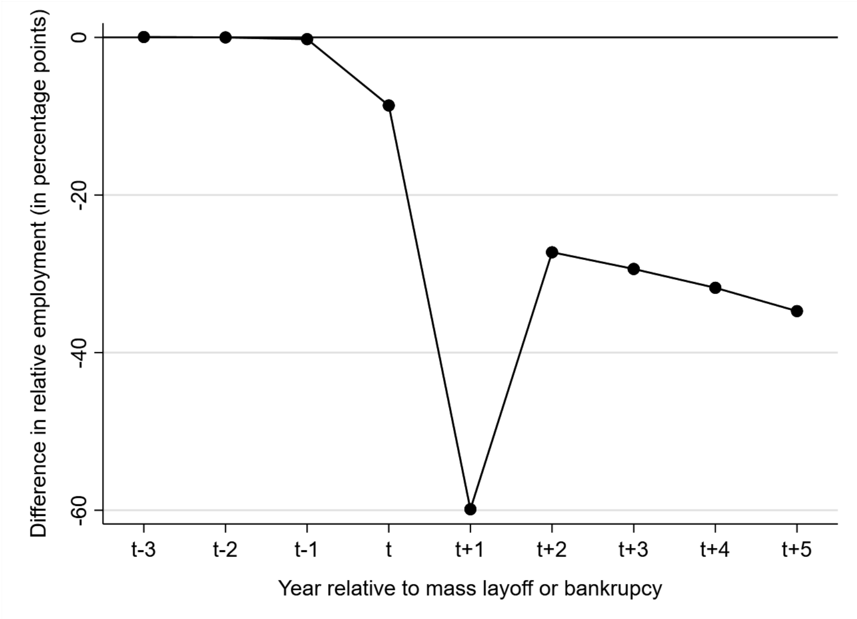
where $log(wage)$ is the logarithm of monthly wages, and the JSI captures the distance between the occupation before displacement and the first job following the event.

4.4 Results

4.4.1 Employment

We now provide baseline estimates of job displacement's impact on relative employment. Figure 4.2 plots the coefficients of the time-to-event dummies from Equation 4.3. 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 4.8 in the Appendix).

Figure 4.2: Effect of displacement on employment

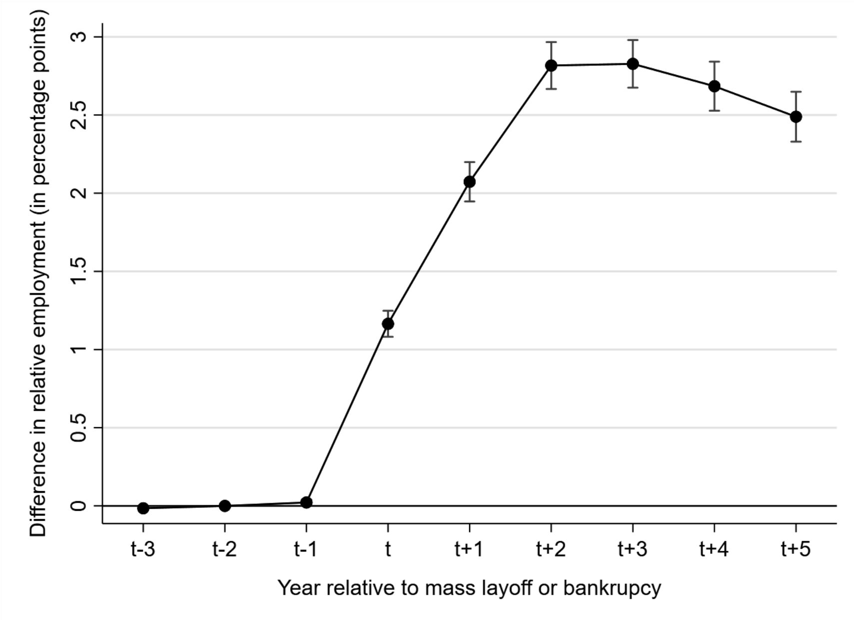


The figure shows the estimates of time-to-displacement dummies from a regression including region, sector, and year fixed effects. The dependent variable is relative employment. Relative employment measures workers' number of months employed in a given year compared to full employment in $t-2$. Year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

4.4.2 Skills commonalities and employment

We are particularly interested in whether the OCI also correlates with shorter periods of unemployment. Figure 4.3 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 4.8 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 4.4 and Figure 4.3, as both the probability of switching occupations and reducing unemployment increases with time.

Figure 4.3: 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, sector, and year 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.

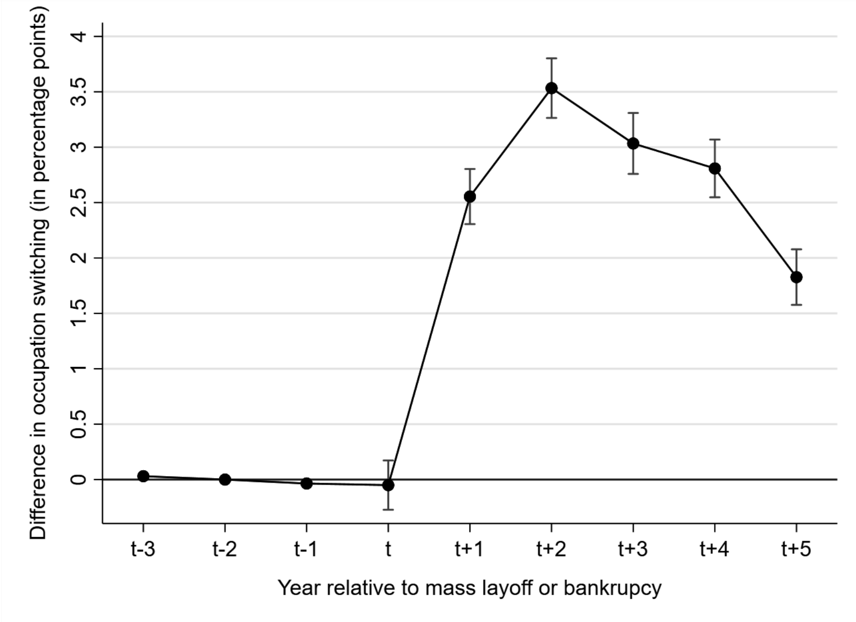
The fact that workers initially search for similar occupations before broadening their job search is illustrated by Figure 4.4. The figure plots the coefficients of the time-to-displacement dummies interacted with the OCI index, taking job switching as the dependent variable. It shows that a higher OCI 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 4.8 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 4.9 shows the most 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 4.10 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.

4.4.3 Occupational distance and wages

The preceding sections primarily examined the relationship between a specific occupation and all potential labor market transitions. Now, we focus on analyzing realized shifts in occupations, as transitioning to distant jobs often negatively affects wages (Guvenen et al., 2020; Huckfeldt, 2018; Lyshol, 2022; Nedelkoska et al., 2015). To assess the impact of moving to distant occupations, we focus on the JSI and estimate Equation 4.4. Figure 4.5 presents the coefficients of the interaction between time-to-displacement dummies and the JSI.

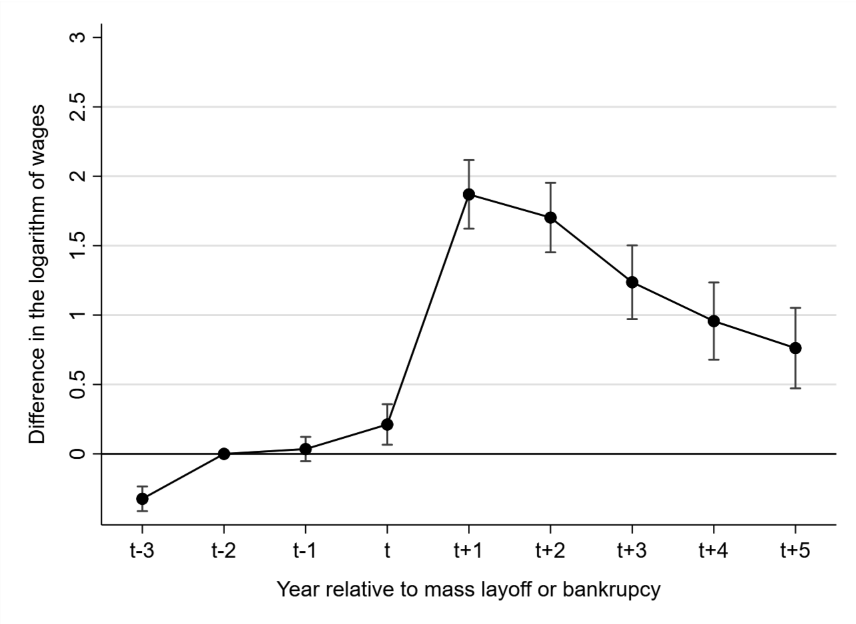
Figure 4.4: Effect of occupational commonality on the probability of switching occupations



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, sector, and year 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.

As the JSI measures the similarity between occupations A and B, the results indeed indicate that moving to more similar occupations reduces the adverse effects of displacement. For instance, a one standard deviation increase in occupations similarity increases workers' wages by about 2% in $t+1$ (see Table 4.11 in the Appendix). It is interesting to note that the coefficient is larger in $t+1$ and that there is some decline over time. This is likely related to the fact that, when moving to distant occupations, workers are more significantly impacted in the short run and that, through learning by doing, they are able to increase wages over time and catch up.

Figure 4.5: 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, sector, and year 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.

4.5 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, 2022; Nedelkoska et al., 2015).

This paper has used a measure of occupational commonality to study the relationship between occupations 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 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 more general occupations, 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. 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, policymakers 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 usefully 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 them in their careers could provide a more robust conclusion. Lastly, further research could also explore the robustness of our findings in different contexts.

[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

4.6 Appendix

Table 4.3: Descriptives by state in the North region of Brazil

	Employer's state						
	11	12	13	14	15	16	17
N	218 (4.1%)	116 (2.2%)	1,636 (30.4%)	42 (0.8%)	3,160 (58.7%)	104 (1.9%)	104 (1.9%)
Treated worker	0.500	0.500	0.500	0.500	0.500	0.500	0.500
Wage	905.228	541.977	1,063.800	675.729	916.839	825.876	938.508
Wage Growth	0.136	0.078	0.055	0.131	0.109	0.060	0.076
Worker's age	32.995	36.112	33.907	35.262	34.186	34.173	32.413
Gender	0.404	0.414	0.218	0.524	0.227	0.462	0.231
Illiterate or primary school	0.000	0.155	0.001	0.095	0.060	0.000	0.019
Primary school graduate	0.174	0.345	0.049	0.381	0.096	0.019	0.096
Middle school graduate	0.202	0.259	0.170	0.238	0.276	0.250	0.231
High-school graduate	0.624	0.241	0.769	0.286	0.550	0.731	0.654
College degree	0.000	0.000	0.011	0.000	0.018	0.000	0.000
Tenure	45.634	41.936	47.644	40.307	49.841	41.403	52.436
Firm's size	311.729	342.103	555.047	97.524	306.816	161.856	140.202
Size (30-49)	0.142	0.112	0.072	0.286	0.148	0.173	0.308
Size (50 - 99)	0.225	0.103	0.097	0.262	0.185	0.298	0.394
Size (100-499)	0.472	0.526	0.401	0.452	0.480	0.529	0.260
Size (500+)	0.161	0.259	0.430	0.000	0.186	0.000	0.038
Firm's average wage	958.011	576.335	1,132.754	650.872	946.549	935.237	882.117
Agriculture and Extractive	0.009	0.000	0.001	0.000	0.044	0.000	0.058
Manufacturing	0.124	0.345	0.302	0.405	0.213	0.173	0.288
Observations	135,566.000	135,566.000	135,566.000	135,566.000	135,566.000	135,566.000	135,566.000

Note: States refer, respectively, to Rondônia, Acre, Amazonas, Roraima, Pará, Amapá, and Tocantins.

Table 4.4: Descriptives by state in the Northeast region of Brazil

	Employer's state								
	21	22	23	24	25	26	27	28	29
N	1,924 (6.1%)	506 (1.6%)	6,146 (19.4%)	1,956 (6.2%)	894 (2.8%)	7,940 (25.1%)	870 (2.7%)	588 (1.9%)	10,850 (34.3%)
Treated worker	0.500	0.500	0.500	0.500	0.500	0.500	0.500	0.500	0.500
Wage	573.570	660.975	804.045	825.351	670.769	816.629	751.850	790.432	947.330
Wage Growth	0.089	0.100	0.095	0.091	0.080	0.098	0.102	0.089	0.103
Worker's age	36.724	35.010	35.099	34.868	34.768	35.131	34.998	34.219	35.084
Gender	0.154	0.229	0.329	0.226	0.376	0.239	0.253	0.231	0.272
Illiterate or primary school	0.034	0.095	0.031	0.036	0.063	0.113	0.216	0.099	0.036
Primary school graduate	0.346	0.312	0.107	0.112	0.139	0.162	0.138	0.129	0.126
Middle school graduate	0.186	0.245	0.235	0.251	0.298	0.205	0.168	0.259	0.228
High-school graduate	0.426	0.324	0.588	0.590	0.463	0.492	0.446	0.486	0.590
College degree	0.007	0.024	0.038	0.011	0.038	0.028	0.032	0.027	0.021
Tenure	157.201	53.019	57.908	53.335	62.248	57.856	59.436	56.813	57.885
Firm's size	1,409.613	661.939	591.212	420.967	388.802	980.410	817.902	181.116	648.131
Size (30-49)	0.103	0.126	0.127	0.142	0.177	0.123	0.155	0.177	0.147
Size (50 - 99)	0.108	0.156	0.155	0.181	0.167	0.139	0.159	0.209	0.185
Size (100-499)	0.237	0.211	0.393	0.461	0.454	0.306	0.420	0.594	0.416
Size (500+)	0.552	0.506	0.325	0.216	0.202	0.431	0.267	0.020	0.252
Firm's average wage	594.372	725.647	851.289	865.417	726.655	872.322	801.281	900.841	986.037
Agriculture and Extractive	0.007	0.020	0.030	0.050	0.036	0.022	0.083	0.027	0.053
Manufacturing	0.057	0.482	0.271	0.165	0.295	0.302	0.301	0.406	0.206
Observations	135,566.000	135,566.000	135,566.000	135,566.000	135,566.000	135,566.000	135,566.000	135,566.000	135,566.000

Note: States refer, respectively, to Maranhão, Piauí, Ceará, Rio Grande do Norte, Paraíba, Pernambuco, Alagoas, Sergipe, and Bahia.

Table 4.5: Descriptives by state in the Southeast region of Brazil

	Employer's state			
	31	32	33	35
N	22,328 (11.7%)	3,120 (1.6%)	34,128 (17.8%)	131,726 (68.9%)
Treated worker	0.500	0.500	0.500	0.500
Wage	1,148.636	1,019.224	1,411.310	1,849.987
Wage Growth	0.111	0.114	0.099	0.108
Worker's age	35.245	35.385	35.729	35.391
Gender	0.280	0.276	0.373	0.322
Illiterate or primary school	0.027	0.014	0.017	0.023
Primary school graduate	0.255	0.178	0.145	0.145
Middle school graduate	0.246	0.338	0.266	0.206
High-school graduate	0.422	0.448	0.462	0.517
College degree	0.051	0.022	0.111	0.109
Tenure	58.176	49.444	61.338	66.594
Firm's size	599.660	479.513	615.879	553.477
Size (30-49)	0.158	0.184	0.141	0.123
Size (50 - 99)	0.171	0.159	0.156	0.173
Size (100-499)	0.404	0.390	0.369	0.393
Size (500+)	0.267	0.267	0.334	0.311
Firm's average wage	1,162.248	1,011.344	1,536.948	1,918.167
Agriculture and Extractive	0.065	0.016	0.009	0.023
Manufacturing	0.370	0.234	0.144	0.428
Observations	135,566.000	135,566.000	135,566.000	135,566.000

Note: States refer, respectively, to Minas Gerais, Espírito Santo, Rio de Janeiro, and São Paulo.

Table 4.6: Descriptives by state in the South region of Brazil

	Employer's state		
	41	42	43
N	13,752 (41.7%)	7,614 (23.1%)	11,624 (35.2%)
Treated worker	0.500	0.500	0.500
Wage	1,129.399	1,211.850	1,215.966
Wage Growth	0.105	0.101	0.096
Worker's age	35.352	35.204	35.684
Gender	0.339	0.420	0.368
Illiterate or primary school	0.014	0.009	0.017
Primary school graduate	0.164	0.221	0.243
Middle school graduate	0.312	0.348	0.276
High-school graduate	0.461	0.366	0.428
College degree	0.048	0.056	0.036
Tenure	58.718	59.154	58.971
Firm's size	672.492	708.021	494.111
Size (30-49)	0.149	0.173	0.135
Size (50 - 99)	0.185	0.208	0.184
Size (100-499)	0.365	0.412	0.412
Size (500+)	0.301	0.208	0.269
Firm's average wage	1,138.592	1,208.430	1,235.907
Agriculture and Extractive	0.007	0.010	0.020
Manufacturing	0.398	0.661	0.513
Observations	135,566.000	135,566.000	135,566.000

Note: States refer, respectively, to Paraná, Santa Catarina, and Rio Grande do Sul.

Table 4.7: Descriptives by state in the Central-west region of Brazil

	Employer's state			
	50	51	52	53
N	750 (7.7%)	1,300 (13.3%)	3,612 (36.9%)	4,124 (42.1%)
Treated worker	0.500	0.500	0.500	0.500
Wage	944.724	1,064.821	1,072.481	1,163.578
Wage Growth	0.115	0.110	0.116	0.102
Worker's age	34.755	34.603	35.124	34.748
Gender	0.459	0.288	0.313	0.232
Illiterate or primary school	0.003	0.031	0.024	0.013
Primary school graduate	0.243	0.217	0.167	0.132
Middle school graduate	0.293	0.278	0.297	0.330
High-school graduate	0.411	0.445	0.481	0.490
College degree	0.051	0.029	0.032	0.035
Tenure	47.368	44.821	56.933	55.418
Firm's size	280.473	629.195	551.861	659.190
Size (30-49)	0.163	0.184	0.136	0.137
Size (50 - 99)	0.183	0.168	0.198	0.152
Size (100-499)	0.436	0.434	0.401	0.359
Size (500+)	0.219	0.215	0.265	0.352
Firm's average wage	955.470	1,078.890	1,088.330	1,178.646
Agriculture and Extractive	0.049	0.088	0.017	0.005
Manufacturing	0.116	0.318	0.283	0.101
Observations	135,566.000	135,566.000	135,566.000	135,566.000

Note: States refer, respectively, to Mato Grosso do Sul, Mato Grosso, Goiás, and Distrito Federal.

Table 4.8: 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 3.2, Figure 4.3, and Figure 4.4. 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 4.9: 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 4.10: 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 4.11: 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 4.4. 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.

5
Exporting and Technology Adoption in Brazil

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Abstract

There is limited evidence about the role that participating in international trade has on the diffusion of technologies. This paper analyzes the impact of exporting on firms' adoption of more sophisticated technologies, using a novel dataset, the Firm-level Adoption of Technology (FAT) survey, that includes more than 1,500 firms from Brazil. The survey provides detailed information about the use of more than 300 technologies, combined with data from the Brazil's census of formal workers (RAIS) and Brazil's exports data from the Ministry of Trade. To address some critical endogeneity concerns, we apply a difference-in-differences with multiple periods to examine the effects of entering export markets on technology adoption. We find that exporting has a positive effects on firms' likelihood of adopting advanced technologies in business functions related with Business Administration, Production Planning, Supply Chain Management and Quality Control, which are important to manage tasks associated to export activities.

JEL Codes: D2, E23, L23, O10, O40
Keywords: Technology, International Trade, Adoption and diffusion

5.1 Introduction

A critical question for economic development is the role of international trade in facilitating the adoption and upgrading of technologies. Participating in international trade can support the diffusion through different channels. Regarding imports, the competitive pressure from increased imports of similar goods can incentivize technology upgrading to diversify to other products but also reduce the rents and push some producers to lower quality segments; thus, disincentivizing innovation and technology adoption. Easier and cheaper access to imports can also facilitate the adoption of new technologies via a reduction in costs and by improving availability of such technologies. In addition, participation in international trade and global value chains (GVCs) can facilitate learning and access to existing technologies via learning from customers in more contested markets or learning from suppliers or buyers.

A rapidly growing literature has explored the links between trade and innovation, as well as technology adoption and upgrading. This literature has explored different channels. The largest share of studies has focused on the impact of imports. Particularly through two specific channels; the impact of imports of intermediate inputs and equipment and the competitive pressure from increasing imports in similar products, such as reductions in tariffs or, more importantly, the China shock. The evidence of these studies is mixed[1], and emphasizes that

[1] Regarding imports, Shu and Steinwender, 2019 summarize the empirical evidence. The authors differentiate between the so-called "Schumpeterian" effect, through which increased competition reduces rents and discourages technology upgrading, and the "escape competition" effect, through which some firms use technology upgrading and innovation to upgrade their products and escape import competition. Their synthesis of the evidence suggests that, in general, increases in imports following trade liberalization tend to be positive on innovation, especially in developing countries (Gorodnichenko et al., 2010) and regarding the imported intermediaries channel. However, in general, the effect of import competition is mixed, especially regarding firms in developed economies. For example, looking at the "China shock", Bloom et al., 2015 find for a sample of firms in 12 European countries that the China competitive pressure positively impacted both technol-

the type of market and the type of firm is critical in understanding the impact on technology adoption and innovation from imports.[2]

A smaller second set of studies, the focus of this paper, analyzes the impact of exports on technology upgrading and innovation. Regarding exports, two important channels are at play. First, a scale effect increases the incentives to adopt new technologies. Bustos, 2011 show how tariff reductions in Argentina in the context of MERCOSUR incentivized firms to adopt new technologies given the larger scale and profits. This positive effect, however, concentrated on firms at the top of the productivity distribution. Lileeva and Trefler, 2010 analyze the impact of tariff reductions in the U.S. on Canadian plants and show that this had a positive impact on exporters, especially on lower productivity plants that are export entrants. Thus, the positive scale effect can also benefit lower productivity plants, but only if they enter export markets. A second channel is the "learning" channel. Atkin et al., 2017 conducts an experimental design with Egyptian rug producers by randomly assigning export contracts and find an increase in quality and learning for those producers that get the export contract.

In sum, this literature finds that there is a positive "learning" effect,

ogy upgrading and reallocation. In contrast, Autor et al., 2020 using a sample of US firms, find the increased competition from China translated into a reduction of technology patents and R&D.

[2] Two sources of heterogeneity are important when looking at the evidence. First, the type of sector competition affects innovation. Aghion et al., 2005 estimate an inverted U relationship between competition and innovation and how more likely competition will affect firms in neck-to-neck competition sectors positively and negatively in laggards. Second and related, more productive firms are more likely to benefit from the impact of trade on technology adoption. Akcigit and Melitz, 2022 develop a model where firms decrease innovation investments when experiencing import shocks. Still, those firms that are better positioned can "escape" this competition by innovating and upgrading. Using data on Indian firms, Bas and Berthou, 2016 find that the trade liberalization process in the 1990s shows how only firms in the middle-upper productivity deciles increased technology adoption and the import of capital goods following tariff cuts in intermediaries. Thus, the firm's productivity level is important for the "escape competition channel" but also the "learning from intermediates" channel.

which also applies to imports of intermediates, and a "scale" effect for exporters that increases their incentives to upgrade their technologies. The evidence summarized in Shu and Steinwender, 2019 finds some evidence for all these channels, with some of the positive effects concentrated among more productive firms.

Identifying the sign and magnitude of the effects of exporting on technology adoption is challenging for three reasons. First, disentangling the causal direction of these effects is difficult, given that more productive firms tend to export and participate in international markets and, accordingly, are more likely to be technologically sophisticated. In addition, in preparation for exporting, firms may upgrade their technologies to generate competitiveness gains and quality upgrades, allowing them to export. A second challenge is the lack of data on technology use. Most of the evidence focuses on indirect technology measures such as patents or R&D; only Bustos, 2011 and Lileeva and Trefler, 2010 use direct technology measures. Third, the use of technology is multidimensional in its application to different business functions. Establishments use different technologies for different tasks, and even within the same business function. Thus, the export effects on technology adoption may differ for different tasks and technologies.

In this paper, we aim to narrow the existing gap in the literature in understanding the relationship between exporting and the technology gap. We use a unique and novel database, the Firm-level Adoption of Technology (FAT) survey, and explore the impact of exporting on technology sophistication and the adoption of selected individual technologies. The survey includes more than 1,500 firms in Brazil and provides granular information on the adoption of more than 300 technologies for different business functions as well as participation in international trading activities.

To address endogeneity concerns, we take advantage of the information collected about the year of adoption of more sophisticated technologies - when adopted - and merge the data with a longitudinal dataset that includes data on export status from Brazil's Ministry of

Trade by firm and year. Moreover, to capture longitudinal information on firms' number of employees and average wages, we combine the dataset with the census of formal workers in Brazil (RAIS). The combined dataset allows us to use a quasi-experimental design to explore the effect of entering export markets on the adoption of sophisticated technologies.

Advancing our key results, we find that entering export markets increases firms' likelihood of adopting advanced technologies linked to Business Administration and production Planning (such as Enterprise Resource Planning (ERP)), Supply Chain Management (such as SRM) and Quality Control.

The paper is structured as follows. Section 2 describes the data. Section 3 provides some initial correlations between exporting and technology use. Section 4 describes the methodology used to identify the impact of exporting on technology. Section 5 shows the main results. The last section concludes.

5.2 Data

5.2.1 The FAT Survey

The Firm-level Adoption of Technology (FAT) survey collects detailed information for a sample of firms about the technologies each firm adopts and uses to perform key business functions necessary to operate in its respective sector (see Cirera et al., 2020). The survey is composed of five modules. Module A collects information on the general characteristics of the firm.[3] Module B focus on technologies used for general business functions regardless of the sector where they operate,

[3]The survey is designed, implemented, and weighted at the establishment level. For multi-establishment firms, the survey targets the establishment randomly selected in the sample.

and sector-specific business functions (module C) focus on technologies that are relevant only for firms in a given sector.[4] Module D focuses on barriers and drivers of technology adoption, while module E gathers information about the firm's balance sheet and employment.

Technology grid

A critical feature of the survey is how technology is measured. To design modules B and C, the FAT survey relies on a group of technology experts to determine the business functions relevant to the firm and the list of technologies that can be used to implement the key tasks in each function, as described by Cirera et al., 2020. We call the resulting structure the *Technology Grid*. The grid in FAT has three characteristics. First, it is comprehensive. It includes the main business functions and the full array of technologies in each function, from the most basic to the most advanced technologies available. Second, the business functions and technologies in the grid are relevant to all firms within any given sector. In addition to identifying the key business functions and relevant technologies, technology experts also provided a ranking of the technologies in each business function based on their sophistication. Overall, the FAT survey covers about 300 technologies split into almost 60 business functions, including general business functions (GBF) that apply to all firms, regardless of the sector, and sector-specific business functions (SBF) applied to agriculture (crops and livestock), manufacturing (food processing, wearing apparel, leather, pharmaceutical, and automotive), and services (retail, accommodation, land transport, banking, and health). section 5.6 shows the grid for GBF and an example of SBF for the food processing sector.

[4]The twelve sectors for which we have developed sector-specific modules are: agriculture and livestock; manufacturing (food processing, wearing apparel, leather and footwear, motor vehicles, and pharmaceuticals); and services (wholesale and retail, financial services, land transport services, accommodation, and health services).

Technology questions

The survey contains three types of questions about the technologies used by the firm. First, FAT asks whether the firm uses each of the technologies in the grid to conduct the tasks of the particular business function. After determining the technologies that are used by the firm in a business function, the survey asks which of these technologies is the most widely used in the business function. Third, when a firm uses an advanced technology in a given business function, the survey asks how many years the technology has been adopted. This allows us to produce three types of measures of sophistication. One regarding all the technologies that are used, extensive measure (EXT); one regarding the most frequently used technology, intensive measure (INT); and finally, the years of adoption for advanced technologies.

A Summary technology sophistication index

As an aggregate indicator to measure sophistication we use a simple cardinal index. Based on the experts' assessment, we order the technologies in each function f according to their sophistication, and assign each a rank $r_f \in 1, 2, ..., R_f$, from least to most advanced. Because several technologies may have the same sophistication, the highest rank in a function R_f may be smaller than the number of possible technologies N_f.[5] We define the relative rank of a technology as $\hat{r}_f = \frac{r_f - 1}{R_f - 1}$. Note that $\hat{r}_f \in [0, 1]$. The technology sophistication of business function f in firm j is a monotonic increasing function of the relative rank

[5] In a small number of business functions, the technologies covered are used in various subgroups of tasks. For example, in the body pressing and welding functions of the automotive sector, the survey differentiates between technologies used for pressing skin panels, pressing structural components and welding the main body. In cases like this, we construct ranks of technologies for each subgroup of tasks within the business function, and then aggregate the resulting indices by taking simple averages across the tasks groups.

of *the most widely used technology* of firm j in function f ($\hat{r}_{f,j}$). For example, our baseline sophistication measure is

$$s_{f,j} = 1 + 4 * \hat{r}_{f,j}. \tag{5.1}$$

Since our baseline sophistication measure is linear, it displays constant increments in sophistication as we move up in the rank. For example, a firm that uses ERP for production planning, the frontier technology has a score of 5, while one that uses specialized planning software would have an index of 4. A priori, the sophistication measures could also be concave or convex in the rank, reflecting diminishing or increasing marginal increments in sophistication as the rank increases. In Cirera et al. (2020), we show how this simple index is robust to alternative cardinalizations.[6] but we use the index only in the descriptive statistics section, moving to adoption of specific advanced technologies in the empirical section.

Sample

We use an original sample of about 1,500 establishments from Brazil. The data includes information from formal establishments in agriculture, manufacturing, and services with at least five employees. Table 5.1 contains detailed information for our sample, disaggregated at narrowly defined industries. For instance, in manufacturing, a large share of establishments are in food processing and wearing apparel, whereas in the services sectors, most establishments are in wholesale and retail. Data were collected face-to-face in 2019 for the state of

[6] The non-uniqueness of latent cardinal variables associated with an ordinal rank such as $\hat{r}_f$ is common in many economic applications such as measures of institutional quality, quality of education, well-being, trust, social norms, and sophistication of management practices, to name a few. However, it is critical to demonstrate that these indices and results are robust to alternative plausible cardinalizations of the ordinal rankings they measure.

Ceará. For the states of São Paulo and Paraná, interviews were carried during 2022.

Table 5.1: Sample distribution by sector

Sector	Frequency	Share
Agriculture	65	4.2%
Livestock	31	2.0%
Food Processing	211	13.8%
Apparel	167	10.9%
Motor vehicles	77	5.0%
Pharmaceuticals	8	0.5%
Wholesale or retail	319	20.8%
Financial services	4	0.3%
Land transport	18	1.2%
Health services	15	1.0%
Other Manufact.	263	17.2%
Other Services	353	23.1%
Total	1531	100%

Note: Table shows the frequency and share of firms by sectors in Brazil in the FAT survey. FAT = Firm-level Adoption of Technology.

In addition to detailed information on the technology used for each business function, the FAT survey also includes information on several firms' characteristics, which we use to control for other covariates likely to explain differences in technology adoption. For example, other than firms' size, region, and sector, the database includes information on managers' and workers' education, the use of formal incentives and performance indicators, and innovation practices, among others.

Table 5.2 offers a description of the information available in the database and presents the main differences between exporters (1,316) and non-exporters (215). For instance, the first four lines describe the gap between exporters and non-exporters for the logarithm of the four technological indexes. Non-exporters show, on average, 11% to 22% lower indexes, are also significantly smaller, interact less with multinational enterprises (MNEs), and receive less government support. Moreover, fewer non-exporters use formal incentives and performance indicators. The gap is also large for managers with a college degree, experience in large companies, or experience abroad. Finally, exporters are more likely to innovate and show a larger share of R&D employees.

5.2.2 Linked longitudinal data

To address endogeneity issues from using only cross-sectional variation in the FAT data, we construct a panel data to exploit additional time variation for the quasi-experimental design while dealing with firm heterogeneity with firm fixed effects. We first merged the FAT with the Relação Anual de Informações Sociais (RAIS) from 1994 to 2020, which is a linked employer-employee data of all registered firms in Brazil. This allows us to construct the panel of firms with firm characteristics that is linked to the year of the adoption of more sophisticated technologies in FAT. We also link the data administrative records from the Brazil's Ministry of Trade to get information on export status at the firm-level across years. The linked longitudinal data from 1994 to 2020 allows us to use a quasi-experimental design (difference-in-differences estimator) to explore the effect of entering export markets on adopting advanced technologies. In essence, we aim to compare the adoption rates of treated firms over the short and medium run with the adoption that would have occurred if they had not started to export. The final dataset includes 215 exporting companies. Of each, 17 are in agriculture, 163 in manufacturing, and 35 in services. Of those, only 25 were already exporters in their first year, thus not switching status.

Table 5.2: Differences between exporters and non-exporters

	Non-exporter		Exporter		
	Mean	Std. Dev.	Mean	Std. Dev.	Difference
GBF EXT	1.10	0.26	1.30	0.19	0.18***
GBF INT	0.84	0.30	1.10	0.24	0.22***
SBF EXT	1.00	0.34	1.20	0.37	0.19***
SBF INT	0.66	0.37	0.77	0.41	0.11***
Number of employees	108.33	334.58	674.35	1480.48	566.01***
Multinational	0.03	0.17	0.15	0.36	0.13***
Interaction with MNEs	0.51	0.50	0.86	0.35	0.35***
Government support	0.14	0.35	0.32	0.47	0.17***
Financial constraints	0.19	0.39	0.20	0.40	0.01
Family company	0.097	0.30	0.15	0.36	0.05*
Formal incentives	0.54	0.50	0.62	0.49	0.08*
Performance indicators	0.40	0.37	0.66	0.36	0.26***
Manager's with college	0.56	0.50	0.74	0.44	0.17***
Manager's experience (years)	24.36	11.51	27.02	14.50	2.66**
Experience in large company	0.30	0.46	0.49	0.50	0.19***
Studied abroad	0.12	0.32	0.28	0.45	0.16***
Share of college-educated employees	0.12	0.15	0.18	0.23	0.07***
Share of R&D employees	0.002	0.01	0.007	0.01	0.01***
Innovation	0.26	0.44	0.60	0.49	0.34***

Note: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Table shows descriptive statistics and differences by exporter status. First rows present the logarithm of the technology indexes including GBF (EXT and INT) and SBF (EXT and INT). The last column is the coefficient of a simple regression of trade status on the variable. GBF EXT = General Business Function Extensive Margin, GBF INT = General Business Function Intensive Margin, SBF EXT = General Business Function Extensive Margin, SBF INT = General Business Function Intensive Margin.

5.3 Methodology

We begin with examining how exporting status is related to technology adoption using using the cross-sectional variation in the FAT data. The data allows us to examine the association between exporting and different levels of technology sophistication across various business functions while controlling for firm characteristics. We use the linear regressions to estimate the association with the following specifications.

$$S_i = \alpha + \delta Export_i + X_i'\beta + u_i \tag{5.2}$$

where S_i is the technology sophistication measured with technology indices (GBF EXT, GBF INT, SBF EXT, and SBF INT) in a firm i, $Export_i$ is an indicator for if a firm participates in exporting market, and the vector X_i is the set of firm characteristics including sector, size, age, multinational and innovation status, use of formal incentives, financial constraint, and manager's education and experience abroad.

Although the FAT data allows to control various firm characteristics that are correlated with both exporting status and technology sophistication, the estimates from linear regressions may suffer from endogeneity issues due to omitted variables and reverse causality. To better identify causality on the effect of entering international markets on the adoption of advanced technologies, we use the linked longitudinal data and exploit the additional time variation created by the years of adoption of advanced technologies and exporting status. The longitudinal data also permits us to control for time invariant unobserved firm heterogeneity with the firm fixed effects.

Specifically, we use an event study and apply the difference-in-differences with multiple periods developed in Callaway and Sant'Anna (2021). As a dependent variable, we focus on adopting advanced technologies for eight general business functions: business administration, production planning, supply chain management, marketing, sales, payment, quality control, and fabrication (only available for firms in manufacturing). The list of technologies for each business function includes: (i) specialized software and ERP for Business Administration; (ii) specialized software and ERP for Production Planning; (iii) non-integrated and integrated Supplier Relation Management (SRM) for Supply Chain Management; Customer Relationship Management software (CRM) and Big data Analytics or Machine learning algorithms for Marketing; (v) computer numerical controlled machine, robots, and advanced manufacturing for Fabrication; (vi) online sales and electronic orders integrated to specialized supply chain management systems for Sales Methods; (vii) online or electronic payment through a bank wire and online payment through platform for Payment Methods; and, (viii) statistical process control with software monitoring and data management and automated systems for inspection for Quality Control. For instance, in the case of business administration, we have information on whether firms adopted specialized software or ERP and, more importantly, the date on which the firm adopted it. Using the years of adoption, we create an indicator for each business function equal to 1 from the year the firm adopted a given advanced technology and 0 in the previous years.

In a typical difference-in-differences setting, we are confronted with two time periods: no firm is treated in the first period, and a group is treated in the second. Nevertheless, in our setting, in addition to multiple periods, firms enter exporting markets at different times, thus creating variation in the treatment timing. Traditionally, the response to this challenge is by estimating a model that includes dummies for crossectional units (α_i) and time periods (α_t) and a treatment dummy (D_{it}). For example, the basic event study model would be:

$$y_{it} = \alpha_i + \alpha_t + \beta^{DD} D_{it} + \epsilon_{it} \tag{5.3}$$

where y_{it} is the outcome of interest. Nevertheless, under the presence of time-varying treatment effects, the difference-in-differences estimator has been found to be biased (Baker et al., 2022; Goodman-Bacon, 2021). In our case, entering export markets could have heterogeneous effects on technology adoption over time, especially considering variation in costs and technology diffusion. To address this issue, we take advantage of recent developments in the difference-in-differences literature and apply the multiple periods estimator proposed by Callaway and Sant'Anna (2021). The method breaks down several treatment periods into group-time average treatment effects (the average treatment effect in period t for the group of units first treated in period g) and aggregates them into meaningful measures of the causal effects.[7] The average treatment effect on the treated (ATT) for a treatment-timing group g is thus:

$$ATT(g,t) = E[Y_t(g) - Y_t(0)|G_g = 1], \text{for } t \geq g \tag{5.4}$$

where G_g denotes the time when unit i receives treatment and $G_g = g$ for all firms that receive treatment at time period g. For instance, take the case where there are five groups, each of which gets treated in 2010, 2011, 2012, 2013, and 2014, and the panel ends in 2016. As a result, the model estimates a total of 15 group-time ATTs – 5 ATT(g,t) for the first group, 4 for the second, 3 for the third, 2 for the fourth, and 1 for the last.[8] In most of our discussion, we focus on a weighted average of post-treatment average effects from t to $t+5$ with weights proportional

[7]Although data from the Ministry of Trade includes information on the first and last year a given firm exported, the method proposed by Callaway and Sant'Anna (2021) assumes that treated units remain treated during all subsequent periods. In our sample, less than 25% of the firms exported for less than two years. We assume that firms' decision to export, even if unsucessul, already impacts their decision to adopt advanced technologies. In addition, as a robustness check, we estimate additional models excluding these firms and find qualitatively similar results.

[8]Under the no-anticipation and parallel trends assumptions, group-time average treatment effects are identified in periods when $t \geq g$ (i.e., post-treatment periods for each group). In practice, we also estimate pseudo group-time pre-trend coefficients (when $t < g$), which we can use to test the parallel trends assumption.

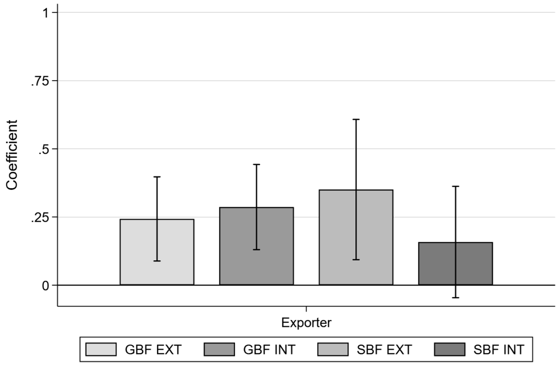
to the group size. The model assumes parallel trends of the potential outcome in the absence of treatment, which we relax to hold only conditional on the covariates. In addition to a dummy indicating firms in the services sector, we add the logarithm of employment and average wages as control variables so that parallel trends hold only after conditioning on a vector of pre-treatment covariates. Finally, estimates use the doubly robust estimator based on stabilized inverse probability weighting and ordinary least squares proposed by Sant'Anna and Zhao (2020).

5.4 Results

5.4.1 Cross-sectional results

Our starting point in exploring the relationship between exporting and the adoption of advanced technologies is looking at the cross-sectional relationship between trade status and the technology index. Figure 5.1 shows the coefficient estimates and 95% confidence intervals from the regressions of the different aggregate technology indices on the exporting status, controlling for sector, dummies for firms' size and age, and additional control variables. The indices include the extensive measure (EXT) and the intensive measure (INT) for both general business function (GBF) and sector specific business function (SBF). The estimates show a positive correlation between exporter status and technology sophistication for all indices.

Figure 5.1: Technology adoption and participation in international trade

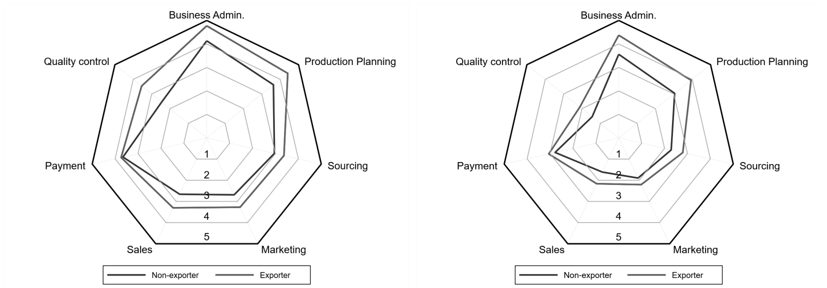


Note: Figure provides the coefficients of exporter status with 95% confidence intervals from the regressions for technology sophistication measures. Each technology measure is regressed on a dummy equal to one if the firm exports. Linear regressions control for sector, size, age, multinational and innovation status, use of formal incentives, financial constraint, and manager's education and experience abroad.

The results show positive associations between exporting status and different technology sophistication measures. Compared to non-exporters, exporters are likely to have 25% or more larger technology indices in general business functions (both extensive and intensive margin) and sector specific business functions (extensive margin). These associations are statistically significant. The association with intensive margin of sector specific business functions is positive, but the magnitude of the coefficient is slightly lower (about 15%) and insignificant. In other words, exporters not only adopt more advanced technologies but also intensively use such technologies to perform general business functions. They also adopt advanced technologies for sector specific business functions, but these technologies may not be used intensively.

To better understand if the technology gap between exporter and non-exporter varies across different types of business functions, we focus on general business functions and examine the averages of both extensive and intensive margins of disaggregated business functions in Figure 5.2. In terms of the extensive margin in Panel (a), exporters tend to have higher levels of technology sophistication in all business functions, except for payment. Particularly, the sophistication level is much higher in administration and production planning. And the gap of the extensive margin is the largest in quality control. Regards to the intensive margin in Panel (b), the average sophistication decreases across for both exporter and non-exporter across all business functions, particularly more in sourcing, marketing, sales, and quality control. But the gap does not disappear. Exporters intensively use more advanced technologies than non-exporters.

Figure 5.2: Technology Sophistication by Business Function by Exporting Status

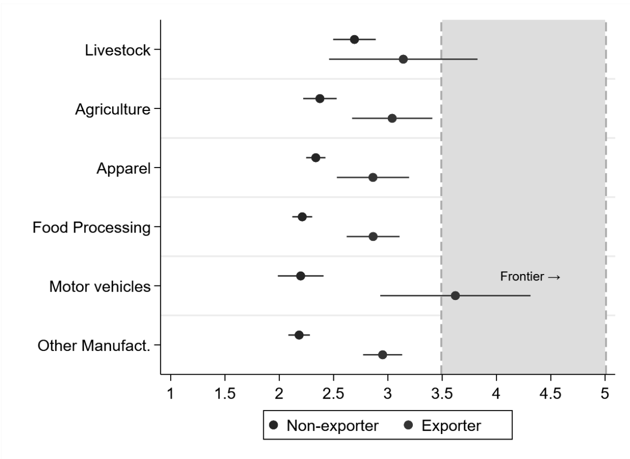


(a) Extensive margin (b) Intensive margin

Note: Figure presents simple averages for each group in each business function.

Finally, Figure 5.3 shows the average technology sophistication measures by sector in the sample, excluding services. Differences between the two exporting status groups are larger in food processing and agriculture. These correlation results are consistent and complement other empirical work in developed economies showing that firms that participate in international trade concentrate a significant number of patents (see Aghion et al., 2018 for French firms) and R&D (see Foster et al., 2020 for US firms).

Figure 5.3: Technology Sophistication of Exporter and Non-exporter by Sector



Note: Each technology measure is regressed on a dummy equals to one if the firm exports. Linear regressions control for sector, size, age, multinational and innovation status, use of formal incentives, financial constraint, and manager's education and experience abroad. We define the frontier as a technology sophistication index higher than 3.5, representing around 5% of firms in our sample.

5.4.2 Difference-in-differences results using linked longitudinal data

The results in the previous sections suggest the potential impact of exporting on the adoption and use of technologies. But even after controlling for several key firm characteristics, the associations could be biased due to contemporaneous shock, omitted variables, or reserve causality. To disentangle the causal effect of trade exporting on technology sophistication, we move on the analyses of the linked longitudinal data.

Table 5.3 shows the main results of estimating the impact of entering export markets on the probability of adopting, which are based on the average treatment effect on the treated from t to $t+5$. We find a positive and significant impact of entering the international market on adopting more sophisticated technologies for most business functions, with particularly large coefficients for Business Administration, Production Planning, Supply Chain Management, and Quality Control. For instance, after starting to export, establishments tend to have a 13.7% larger propensity of adopting specialized software or ERP for Business Administration, compared to those not exporting.[9] Moreover, in the case of Quality Control, the export status is associated with a 8.9% larger probability of adopting statistical process control with software monitoring and data management or automated systems for inspection. It is also interesting to note that coefficients are positive for all business functions - although not statistically significant in some cases.

[9] When excluding firms that exported for less than two years, we find a coefficient of 0.126 and statistically significant at 5%.

Table 5.3: Effect of exporting on the adoption of advanced technologies for business functions

	(1) Business Administration	(2) Production Planning	(3) Supply Chain	(4) Marketing	(5) Sales	(6) Payment	(7) Quality Control	(8) Fabrication
ATT	0.137***	0.065**	0.063**	0.035	0.043*	0.025	0.089***	0.008
	(0.043)	(0.033)	(0.029)	(0.023)	(0.026)	(0.033)	(0.028)	(0.043)
N	19,916	19,916	19,916	19,916	19,916	19,916	19,916	2,183

Note: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Table shows the estimates of the ATT from the difference-in-differences with multiple time periods. In columns (1)-(7), the sample includes all firms in the FAT data linked to trade and employer-employee data. In column (8), the sample includes manufacturing firms in the linked data. For each business function, the dependent variable is a dummy equal to 1 if a firm adopts the advanced technologies from the year and 0 otherwise. Specifications control the logarithm of wages, the logarithm of total employment, and a dummy for the services sector. Robust standard errors are in parentheses. ATT = Average Treatment on the Treated.

Figure 5.4.2 panel (a) shows the disaggregated coefficient estimates for Business Administration from $t-5$ to $t+5$ from the event study. The results indicate that during the years before treatment, coefficients are not statistically different from zero, which we interpret as an indication that the parallel trends assumption holds and that there is no anticipation effect. In contrast, following the treatment, we observe a clear positive effect, which increases over time. The results are consistent with a model in which export increases firms' managerial layers (Caliendo & Rossi-Hansberg, 2012; Garicano & Rossi-Hansberg, 2014). To cope with more complex tasks induced by trade participation, firms raise the number of managers and adopt more sophisticated technologies for business administration.[10] Results are also consistent with the scale effect channel, through which larger demand induces the adoption of new technologies (Bustos, 2011).

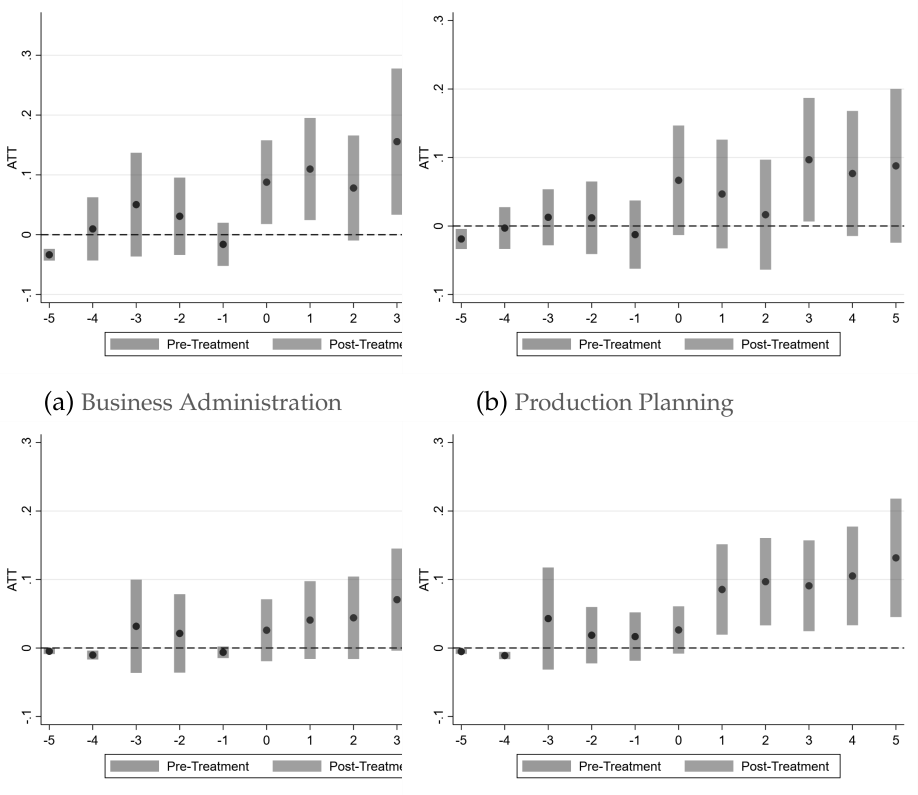
We also find similar results for Quality Control technologies. Coeffi-

[10]section 5.7 shows that firms that enter exporting markets increase the number of knowledge hierarchies, consistent with our hypothesis that technology adoption is related to the increased complexity associated with exporting.

cients are positive from t to $t+5$, without signs of preparation to export. The findings align with the literature showing that firms raise product quality as they enter international markets (Álvarez & Fuentes, 2011). Export markets carry higher quality requirements, and exporting firms produce higher-quality products by increasing the quality of their inputs and varying the quality of their products across destinations (M. Kugler & Verhoogen, 2008; Manova & Zhang, 2012).[11] Our results show that as firms adapt to more restrictive quality standards, they adopt more advanced technologies for quality control.

[11] In fact, Iacovone and Smarzynska Javorcik (2012) shows that firms raise output prices two years before entering exporting markets, which suggests that the quality-upgrading process takes place in preparation to export.

Figure 5.4: Effect of exporting on the adoption of advanced technologies



(a) Business Administration

(b) Production Planning

(c) Supply Chain Management

(d) Quality Control

Note: The figure shows the estimates of the interaction between time-to-event dummies and a treatment indicator from a regression including firm fixed effects, time-to-event dummies, and year fixed effects. Estimates also include a dummy for the services sector, the logarithm of wages, and the logarithm of total employment as controls. The dependent variable is a dummy equal to 1 if the establishment adopted a advanced technology in each business function. Vertical bars show estimated 95% confidence intervals.

Finally, the positive effect on the adoption of advanced technologies in Production Planning and Supply Chain Management is likely to be associated with the need to manage more efficiently and timely the production process and the increasing number of buyers and suppliers. For instance, availability of high-quality intermediate goods is often limited in developing countries' local markets. As firms enter export markets, they not only engage with additional buyers but are also likely to expand the range of suppliers to acquire better intermediate goods and better manage risks associated to disruptions in the supply chain, since the costs of not fulfilling export orders are higher.

5.5 Conclusions

Understanding the role that participating in international trade has in the diffusion of advanced technologies is critical for developing countries. But while a large literature has focused on the import channels for diffusion and adoption, much less is known on the role of entering export markets in facilitating this diffusion and adoption of new technologies. This paper aims to fill the gap in this literature by identifying the impact of exporting on the adoption of more sophisticated technologies in Brazil.

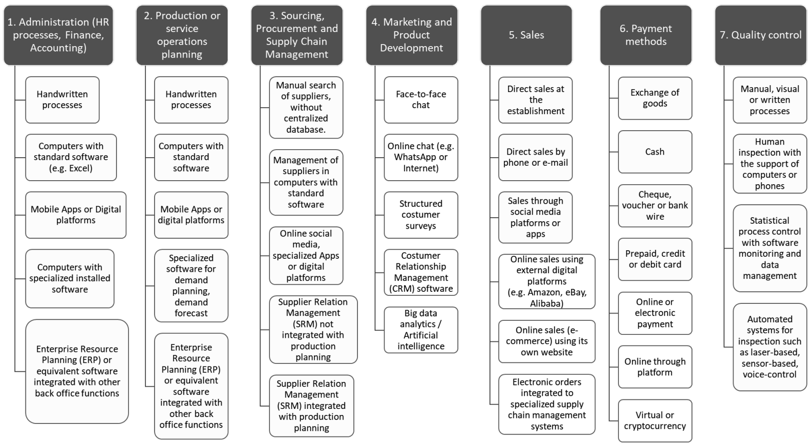
Using a novel dataset with longitudinal information on exporting and technology use, and implementing a difference-in-differences estimator to a sub-sample of establishments in Brazil, we find a positive and statistically significant effect in the likelihood of adopting sophisticated technologies in key business functions for exporting. For example, starting to export is associated with a 13.7% larger probability of adopting specialized software or ERP for Business Administration; and an 8.9% larger probability of adopting statistical process control with software monitoring and data management for inspection in quality control. We also find positive and significant effects on the probability of adoption in Production Planning or Supply Chain Management. The evidence presented is consistent with models that suggest that exporting increases the complexity of tasks and processes within the firm, and these requires better technologies to aid managing these tasks and processes.

While the evidence presented here is also aligned with other empirical work showing a positive impact of exporting on innovation; more evidence is needed to identify the key channels that explain this positive relationship. For example, what is the role that international buyers play in transferring these more advanced technologies, or what role does competing in more contested international markets play in incentivizing technology upgrading.

5.6 Appendix A

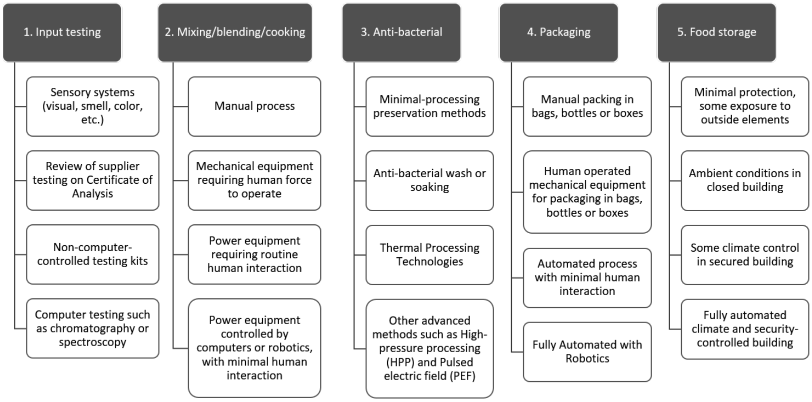
Figure 5.5 shows the grid for general business functions that all firms, regardless of the sector, respond. Figure 5.6 shows one example of sector-specific business functions for the food processing sector.

Figure 5.5: General Business Functions and Their Technologies



Source: Cirera et al. (2020)

Figure 5.6: Sector Specific Business Functions and Technologies in Food Processing



Source: Cirera et al. (2020)

5.7 Appendix B

To check for the link between exporting and firms' complexity, we leverage the detailed information on workers' occupations and test whether firms that started exporting also increased knowledge hierarchies. We define firms' number of knowledge hierarchies based on Caliendo et al. (2015) and Cruz et al. (2018) (see Table 5.4).

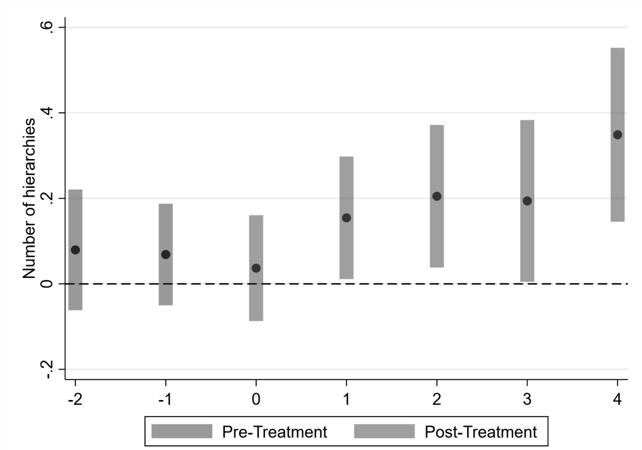
We then apply a similar model as in Equation 5.3 and take the number of hierarchies as the dependent variable. Figure 5.7 shows the main results, suggesting that there is an increase in the number of knowledge hierarchies associated with firms' exporting activities.

Table 5.4: Classification of layers

	(1) CBO	(2) Hierarchy	(3) Layer	(4) % College-educated
CEO and managers	G1	H5	L4	42.2%
Professional	G2	H4	L3	81.9%
Technicians	G3	H3	L2	17.7%
Clerks and services	G4 and G5	H2	L1	5.9%
Production workers	G6, G7, G8, and G9	H1	L0	0.9%

Source: Authors' elaboration based on Cruz et al. (2018). Column (4) shows the share of college-educated workers in each group for the year 2011.

Figure 5.7: Effect of exporting on the adoption of advanced technologies



Note: The figure shows the estimates of the interaction between time-to-event dummies and a treatment indicator from a regression including firm fixed effects, time-to-event dummies, and year fixed effects. Estimates also include a dummy for the services sector, the logarithm of wages, and the logarithm of total employment as controls. The dependent variable is the number of knowledge hierarchies. Vertical bars show estimated 95% confidence intervals.

6 Conclusion

Johnson and Acemoglu (2023, p.202) highlight that "[technology] can generate shared prosperity or relentless inequality, depending on how they are used and where new innovative effort is directed." This dissertation uses a series of novel datasets and applies robust methodologies to examine the intricate interplay between technology adoption, skills, and labor market dynamics in an attempt to assist policymakers in designing well-suited policies to address these challenges.

Chapter 2 delves into the topic of job polarization within emerging and developing economies. I first review the existing empirical literature, revealing that job polarization is only at an early stage in these countries. I then engage in a theoretical discussion to explain the reasons behind this process. Firstly, it becomes apparent that the lower adoption of advanced technologies in developing and emerging economies contributes to the disparities in employment changes. Secondly, while developed economies have seen a shift from manufacturing to service employment, many emerging and developing economies continue to industrialize, leading to different job demands. Lastly, the offshoring of routine, middle-earning jobs from advanced economies to developing ones has further reduced the rate of job polarization. These three factors largely explain the differences between developed and developing economies.

I then discuss the main gaps in the empirical literature and stress the importance of more systematic and frequent micro-level data collection to understand better the task content of occupations specific to each country and the patterns of technology adoption. These studies would enhance our understanding of the main barriers to technology adoption and the adverse effects at the worker level, thus allowing for the development and implementation of better-adapted policies fitted to developing and emerging economies' specific contexts.

Chapter 3 addresses one of these gaps and focuses on the adverse impact of job displacement and mass layoffs for workers in routine-intensive occupations. Despite Brazil's lack of job polarization, the country is one of the few developing economies that already show signs of a relevant decline in the demand for routine-intensive occupations. More importantly, rather than focusing on aggregate measures of polarization, it is crucial to explore the individual-level effects of this process, examining the extent to which workers are affected and their ability to transition to different jobs without facing prolonged periods of unemployment and lower wages.

Using a large sample of displaced workers and applying difference-in-differences models, the study reveals that job displacement significantly impacts wages and employment opportunities in the short and medium run. Displaced workers experience wage declines even five years after the displacement event, and they are more likely to face prolonged periods of unemployment. Due to advancements in technology adoption, particularly those that replace routine tasks, workers in routine-intensive occupations face more severe negative outcomes. Those in routine-intensive occupations face larger wage declines, prolonged unemployment, and a larger probability of switching occupations.

The findings emphasize the vulnerability of routine workers and the importance of reskilling initiatives to mitigate the negative impacts of displacement. In particular, they highlight the need for educational policies to adequately equip the labor force with the necessary skills to guarantee maximum benefits from new technological advancements and facilitate workers' transitions aimed at technology adoption. However, upskilling the labor force to adapt to the changing requirements can only partially rely on early education. There should be opportunities to develop competencies beyond specific tasks, especially retraining programs for adults, ensuring lifelong learning systems. Furthermore, policymakers can establish effective social safety nets to protect workers adversely affected by technological disruptions. Robust social protection programs, such as unemployment benefits, job retraining assistance, and income support, can help mitigate the negative consequences of technology-induced job displacement.

In line with workers' transitions across occupations, Chapter 4 focuses on labor market mobility, examining the transferability of workers' occupational skills to other occupations. To this end, I first developed a commonality index utilizing detailed information on occupational skills based on O*NET. Then, I use a sample of displaced workers due to mass layoffs or firm closure and employ an event-study methodology to investigate the significance of occupational skills commonality on labor outcomes. The findings reveal that workers possessing a more specialized skill set tend to experience more extended periods of unemployment and are less inclined to switch to different occupations. Additionally, I investigate the impact of occupational mismatch on workers' wages. I find that transitioning to more distant occupations negatively affects salaries. However, this negative effect is somewhat mitigated by the learning efforts of workers and firms' revision of their expectations as workers gain experience.

A nuanced understanding of skill transferability has substantial implications for policymaking. By recognizing the potential for skills to cross occupational boundaries, policymakers can design targeted training programs, offer comprehensive career guidance services, and enhance labor market information systems. These efforts empower unemployed individuals to explore a wider range of job opportunities, align their existing skills with new occupations, and increase their chances of successful reemployment. By leveraging this knowledge, policymakers can foster a more resilient labor market and facilitate the smooth transition of workers during periods of structural change.

Finally, Chapter 5 analyzes the impact of engaging in international trade on technology adoption among firms in Brazil. I use a novel dataset of technology adoption at the business-function level and combine it with information on firms' employment and exporting status. Applying difference-in-differences models, I find that entering export markets is associated with a higher probability of adopting more sophisticated technologies related to a number of business functions, in particular, quality control and business administration. For instance, firms that start to export are more likely to adopt Enterprise Resource Planning (ERP) systems. Overall, the results suggest that exporting enhances the complexity of tasks and processes within firms, necessitating the adoption of better technologies to manage these challenges effectively.

The results underscore the crucial role of international trade in facilitating technology adoption and offer some important insights for policymakers. For instance, policymakers can implement measures to support firms' engagement in international trade and simultaneously enhance their technological capabilities, building the physical, human, and institutional capacities required for the adoption of more sophisticated technologies. For example, streamlined export promotion policies should be complemented with policies to reduce information asymmetries about existing and more suitable technologies. Concurrently, investment in skills and managerial capabilities can increase firms' absorptive capacity and smooth the integration and diffusion of advanced technologies. These complementary aspects may be particularly relevant in the context of developing economies, given that most technologies were developed in high-income economies and tailored to those economies' organizational and institutional environments. Furthermore, the study emphasizes the need for further research to identify the key channels that explain the positive relationship between international trade and technology adoption.

Finally, there are numerous ways to expand the research presented here. First, Chapter 3 assumes that the task content across occupations is similar across countries and uses a routine-intensity task index based on data from the U.S. Even though we argue that this issue is less problematic in the context of Brazil, future research could explore different measures of routine task intensity that are better suited for the context of developing countries. Moreover, Chapter 3 presents individual-level evidence of how technological change has affected workers in routine-intensive occupations. Further research may connect direct instances of technology adoption at the firm level rather than relying solely on changes in occupational skill demands. In turn, future studies could explore more in detail changes in the skill demand at the firm level and investigate how particular technologies impact the employment outcomes of different worker groups.

As for Chapter 4, future research should explore beyond the sole definition of occupation-related skills, as those may underestimate workers' full range of skills. To draw more robust conclusions, a dataset that directly links skills to individual workers and tracks them throughout their careers would be valuable. Finally, it would be beneficial for further research to explore the validity of our findings in diverse contexts. For instance, in Chapters 3 and 4, a common path for further analysis is the introduction of the informal sector, as it represents a large share of the labor market in developing and emerging economies.

Finally, related to Chapter 5, other studies can explore the links between trade and technology adoption more in-depth, focusing on differences between destination and volume exported. This would allow us to delve into the distinct role of different international buyers in facilitating the transfer of advanced technologies to firms. Additionally, it would be valuable to investigate the direct effects of technology adoption on firms' performance and the extent to which new exporters encourage technological advancements among non-exporting peers.

7
Impact Paragraph

The impact paragraph of this doctoral dissertation is added in compliance with article 22.5 of the "Regulations for obtaining the doctoral degree at Maastricht University" decreed by resolution of the board of deans, dated 1 October 2020.

This dissertation explores the multifaceted aspects of technology adoption, encompassing its drivers, labor market ramifications, and the pivotal role of skills in enhancing workers' resilience to technological change. In particular, I focus on developing and emerging economies and build on recent findings indicating that technological advancements threaten to displace workers in certain occupations and exacerbate inequality. The importance of comprehending the labor market repercussions of technological change is particularly pronounced in emerging and developing economies, where inequality and unemployment are already exceptionally high. Additionally, these economies grapple with frail social protection systems and educational structures that lack the capacity and agility to respond to shifts in the nature of work.

Hence, this dissertation emphasizes the importance of policymakers' broad and coordinated approach to promoting shared prosperity and addressing the intricate relationship between technology and employment and inequality in the context of developing and emerging economies. In Chapter 2, I study the extent of job polarization in developing and emerging economies. Through an extended literature review, I highlight several gaps in the empirical literature and emphasize the importance of systematically and frequently collecting micro-level data to comprehend occupation-specific task content and technology adoption patterns at the firm level. This data would not only shed light on the obstacles hindering technology adoption but also lay the groundwork for tailored policy interventions specifically designed to address the unique challenges developing and emerging economies face. Furthermore, this data would enable a deeper understanding of the intricate connections between adopting particular technologies and their impacts on the demand for specific skill sets.

Chapter 3 provides evidence that recent technological advancements affect workers in routine-intensive occupations, leading to prolonged unemployment and reducing wages upon reemployment. These findings show the necessity to implement policies focusing on upskilling the workforce, particularly those in routine-intensive occupations. These policies should prioritize assisting these workers through lifelong learning initiatives and re-training programs to mitigate the adverse consequences of job displacement. Furthermore, a nuanced comprehension of the specific tasks undertaken by these groups is essential, particularly recognizing the significance of soft skills that facilitate smoother transitions between jobs.

Chapter 4 presents evidence that the commonality of workers' skills is pivotal in facilitating their reentry into the labor market following a layoff. The findings emphasize the crucial roles played by both public and private employment agencies in expediting job placement and enhancing the prospects of job-seekers finding positions that align more closely with their skill sets. For workers in occupations with higher commonality, intermediation services can advise them to broaden their search. In contrast, for workers in low-commonality occupations, the results also underscore the necessity of reskilling, ensuring they remain competitive and adaptable in a rapidly evolving job market.

Lastly, Chapter 5 examines the drivers of technology adoption at the firm level, mainly focusing on the impact of international trade engagement on firms' decisions to adopt advanced technologies. Notably, the study finds that initiating exports enhances the likelihood of firms adopting sophisticated technologies. These findings shed light on the connection between trade activities and productivity growth, with the adoption of sophisticated technologies playing an important role in this dynamic. Moreover, the results underline the significance of policies that combine export promotion with initiatives to mitigate barriers to technology adoption.

In conclusion, from the importance of upskilling and lifelong learning to the role of trade in spurring technology adoption, the insights from this dissertation provide valuable direction for public policies promoting technology adoption while mitigating its adverse effects on the labor market. The hope is that the findings from this dissertation will contribute to the development of well-crafted programs and effective policies, aiding policymakers in making informed and prudent choices.

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