# Corporate Takeovers and Labor Restructuring

**Abstract**

Using detailed employer-employee administrative data linked with manually-collected information on merger activity in Brazil, I create input-based measures of technological and organizational changes to examine the relation between firms' human capital composition and mergers. I find that firms with larger shares of high-skilled and innovation-intensive employees participate in mergers. Occupational proximity is an important driver of the transaction incidence. Examining post-merger human capital compositional shifts in target firms, I provide evidence on efficiency-seeking restructuring through technology adoption, investment in innovation and cost synergies. I find support for knowledge transfers, management changes and scale economies as potential mechanisms behind these shifts.

# 1 Introduction

Mergers and acquisitions reallocate control over the factors of production, affecting the boundaries of the firm and acting as vehicles for extensive organizational changes in the trajectory of a firm. Previous studies have primarily focused on the reorganization of physical assets (Kaplan and Weisbach, 1992; Maksimovic et al., 2011). However, given the increasing importance of human capital in productivity growth (Zingales, 2000), restructuring of the labor force is arguably an important driver of merger activity and a source of value creation in mergers (e.g., Dessaint et al., 2017; Tate and Yang, 2016). Although the existing literature provides important insights into the role of human capital in mergers, evidence is largely limited to the study of overall employment levels and average wages,[1] thus offering scarce granular insight on changes in employee composition. In this paper, I analyze detailed longitudinal data on employee characteristics and occupational tasks to develop labor-input-based measures of organizational changes and occupational overlap. Subsequently, I am able to provide direct evidence on the relation between a firm's human capital and the decision to merge and offer an in-depth analysis of ex post changes in the composition of a firm's labor force and organizational boundaries.

Existing theories on the role of mergers broadly offer two diverging views regarding the link between mergers and human capital. Agency theories argue that mergers are driven by non-efficiency considerations such as empire-building, managerial hubris, market power and wealth transfers,[2] suggesting a limited role of human capital and labor force restructuring as a merger motivation. Neoclassical theories, instead, maintain that mergers are based on value-maximizing considerations by generating efficiency gains from better use of production inputs. Prior literature has highlighted that mergers foster technological change and knowledge transfers,[3] mitigate agency problems at target firms,[4] exploit complementarities (Rhodes-Kropf and Robinson, 2008), and alleviate financial constraints (Almeida et al., 2011). These theories suggest that merger pairs are likely formed between firms with overlapping human capital, transferring control of human capital resources from technologically lagging to technologically advanced firms. Therefore, mergers potentially change the employee composition in a direction that reflects production advancements and operational synergies through knowledge transfers, technology adoption, lower innovation costs and occupational complementarities.

Exploring the role of human capital characteristics in mergers has been challenging due to lack of detailed information on employer-employee relationships. For my analysis, I draw

[1] For example, see Brown and Medoff (1988), Lichtenberg and Siegel (1990), McGuckin and Nguyen (2001), Conyon et al. (2002) and Li (2013)

[2] For example, see Jensen (1986), Roll (1986) and Shleifer and Summers (1988).

[3] For example, see Gort (1969), Jovanovic and Rousseau (2002), Holmstrom and Roberts (1998), Guadalupe et al. (2012).

[4] For example, see Jensen and Ruback (1983), Bertrand and Mullainathan (2003).

insights from merger activity in Brazil, which is a setting that provides important benefits in exploring the type of changes in employee composition implemented after mergers. First, a primary advantage is the availability of a longitudinal administrative employer-employee dataset that consists of the universe of formal employment and allows me to investigate firms' employment decisions at an unusual level of detail. A distinctive feature of the data is that I observe detailed information on employee characteristics, occupations, employment inceptions and terminations, which is critical to systematically isolate a firm's labor demand across different employee groups and create input-based measures that capture several mechanisms behind any changes in the human capital composition. Second, the presence of intense merger activity during the sample period (a large part of which originates from developed countries) along with the fact that Brazil is a high-growth economy and a nation of 200 million people makes the setting interesting in its own right to explore post-merger restructuring of labor inputs. Specifically, by combining manually collected information on the identity of both public and private firms involved in merger activity from 2004 to 2012 with the administrative data, I am able to follow the characteristics of employees who separate, join, and remain in target firms in the period around the merger, and directly measure the relation between mergers and the composition of the labor force across several important dimensions.

A primary contribution of the paper is that I rely on comprehensive information on employee characteristics and textual analysis of the description of tasks performed by 2,500 occupations to develop novel input-based measures that capture several dimensions of organizational change, including skill and routine intensity, investment in innovation, and potential synergistic gains stemming from pairwise, within- and across-sector occupational overlap. The underlying assumption is that changes in the production process are expected to manifest in meaningful changes in occupational shares and demand for employees that have certain attributes or perform certain types of tasks. For example, the acquisition of Bompreço, a major retail chain, by Walmart was followed by automation through the installation of self-checkout kiosks leading to a decline in the share of employees performing repetitive tasks (cashiers).[5] Relatedly, KWS Saat fostered innovation activity in the acquired Brazilian firms though knowledge transfers leading to an increase in demand for occupational tasks related to research and development. Finally, the merger of financial institutions Itaú and Unibanco was motivated by both cost-based synergies due to the large degree of occupational overlap in retail banking and efficiency gains arising from differentiation and complementarity in operations and human capital.[6]

The first set of findings provides strong evidence of positive selection, assortative matching and complementarities among transacting firms in terms of human capital characteristics.

[5]See https://www1.folha.uol.com.br/fsp/dinheiro/fi0203200411.htm.

[6]Itaú was stronger in investment banking and auto loans, while Unibanco was stronger in the areas of insurance and consumer finance (Villalonga et al., 2012).

While acquirers are generally larger and employ a greater share of high-skilled labor compared to target firms ("high-buys-low"), both are significantly larger and have a greater share of high-skilled and innovation-intensive employees compared to peer firms ("positive selection"). The only exception is in the adoption of labor-saving technology with acquirers exhibiting lower and target firms higher routine intensity compared to peer firms. Focusing on the role of human capital overlap between merger participants, I find the transaction incidence is higher between firms that have greater pairwise occupational, skill and routine proximity ("assortative matching"). An important contribution of the paper is to highlight that firms that are broadly similar in terms of human capital to the population of firms but less similar to rival firms are more likely to be acquirers or target firms, suggesting that between-sector human capital proximity and within-sector human capital differentiation are important determinants of mergers ("complementarities").

Having established the presence of selection effects in the decision to merge, I characterize the extent and direction of labor restructuring over the five-year post-merger period. My identification strategy follows Davis et al. (2014) and Graham et al. (2019), and relies on matching firms that were targets of mergers with comparable firms that have never been involved in a merger in an event-study difference-in-differences specification. The matching strategy allows me to identify a set of counterfactual firms based on interactions among observable characteristics including employment, sector, business type, and multi-establishment status. In addition, I control for a variety of time-varying characteristics and employ various fixed effects to isolate potential sources of identifying variation. Using this research design, I am able to compare changes in the composition of human capital and the organizational boundaries of target and control firms over time in the period around the merger.

I report three central findings that suggest acquirers actively restructure target firms' labor force in an efficiency-seeking direction reflecting skill upgrade, technology adoption, investment in innovation and cost synergies. First, in line with the disproportionate importance of high-skilled employees for productivity, I find that target firms are able to retain and attract high-skilled employees, as reflected by an economically significant increase of 8.6% relative to the sample mean in the share of high-skilled employees.

Second, I relate skill upgrade with technology adoption by distinguishing between multiple facets of technological change that have different implications for the labor composition. Examining the role of skill-biased technological change (Katz and Autor, 1999), I find that mergers are followed by an increase in demand for employees in knowledge-intensive occupations leading to an economically important increase in the post-merger share of 12% relative to the sample mean. Relatedly, mergers act as vehicles for fostering innovation by increasing demand for employees in innovation-intensive occupations. Consistent with recent literature that highlights the role of technological modernization in displacing employees that perform routine occupational tasks (Autor and Dorn, 2013), I provide evidence of an economically

significant decline in routine intensity of 5.9 log points and an increase in demand for occupations that require skills complementary to information technology (IT).

Third, I provide evidence of organizational streamlining by considering the role of cost synergies from duplicate occupations and the resolution of agency frictions induced by inefficient or entrenched managers as potential sources of value creation. I find that occupational overlap is an important determinant of involuntary separations as employees in mergers with a high degree of occupational proximity experience an economically significant increase of 33% in the probability of involuntary separation. I next use textual analysis to distinguish between high-level (e.g., CEOs) and lower-level managers (e.g., supervisors) by identifying occupations that involve tasks related to supervision, monitoring and coordination of employees. I find that acquirers replace incumbent high-level managers but retain supervisors in target firms.

Examining the dynamic effects of mergers, I find no evidence of pre-treatment trends in the evolution of human capital characteristics. Changes in human capital composition occur at the year of the merger, gradually increase in magnitudes over time and never revert in the five-year period after the merger. I also attempt to relate post-merger changes to efficiency gains by providing suggestive evidence that mergers are associated with increases in innovation efficiency using information on patenting activity from the Brazilian Patent Office. Overall, my findings provide support for neoclassical theories of mergers that point to efficiency-enhancing technological and organizational change driving the observed compositional changes in target firms' human capital.

I explore several non-mutually exclusive mechanisms behind the observed compositional changes. First, to the extent that shifts in human capital are driven by acquirers transferring technology, knowledge and organizational practices to target firms, the effects are expected to be larger in mergers where acquirers have greater potential and ability to do so. As predicted, I find that post-merger changes are concentrated on mergers (i) where pre-merger differences in skill, routine and innovation intensity between acquirers and target firms are larger, and (ii) where the acquirer is technologically advanced or a foreign firm.

Second, I find that mergers in which target firms hire managers in roles related to research and development and information technology are associated with larger changes in the share of employees that perform innovation-intensive and routine tasks, suggesting that acquirers actively invest in expertise to impose production advancements.

Finally, I consider the role of scale economies and financial efficiencies in facilitating investment in technology. To the extent that the presence of duplicate employees decreases the relative price of technological upgrade and enables target firms to invest in labor-saving technologies, I expect employees in overlapping occupations that perform tasks substitutable by technology to experience a post-merger increase in involuntary separations. Indeed, I find

that occupational overlap increases involuntary separations only for employees that perform routine and less knowledge-intensive tasks. I also find that the merger effects are concentrated on smaller firms, consistent with the relaxation of financial constraints as a potential mechanism through which mergers foster technological investment.

The paper contributes to the literature that examines the process of post-merger restructuring (Kaplan and Weisbach, 1992; Maksimovic et al., 2011). Existing papers are primarily concentrated on physical assets and find that mergers are followed by extensive restructuring through the disposition of a large number of acquired establishments. I also add to the literature on finance and labor[7] and, specifically, the set of papers that examine the link between mergers and human capital. A central finding of this line of research is that human-capital considerations and labor restructuring are important drivers of merger activity and synergy gains (e.g., Li, 2013; Dessaint et al., 2017; Ouimet and Zarutskie, 2016; Tate and Yang, 2016; Lee et al., 2018).[8] In particular, a set of contemporaneous papers provides direct evidence on the impact of mergers on employees and wage growth, emphasizing the role of labor market concentration (e.g., Prager and Schmitt, 2021; Arnold, 2020) and occupational shifts that lead to increases in inequality (e.g., Ma et al., 2019). Finally, I contribute to the existing literature that investigates the precise channels through which synergy gains materialize in mergers (e.g., Hoberg and Phillips, 2010; Sheen, 2014; Bena and Li, 2014).

My paper complements these strands of literature on three distinct dimensions. First, I use detailed employee-level longitudinal administrative data to provide systematic evidence on the relation between human capital characteristics and the decision to engage in a merger. Tate and Yang (2016) focuses on the role of cross-industry labor mobility in explaining corporate diversification. Lee et al. (2018) combines information on the distribution of occupations at the industry level with segment data from Compustat to highlight the role of human capital relatedness as a motivation for mergers between firms that operate in unrelated industries or product markets. A critical limitation is that the measure of human capital relatedness relies on the assumption that the distribution of occupations at the industry level reasonably captures the distribution of occupations for a firm in the industry. I extend the literature by leveraging administrative employer-employee data to construct firm-level measures of pairwise skill and occupational proximity, and provide evidence of positive selection and assortative matching among transacting firms in terms of human capital characteristics. Importantly, I highlight the importance of human capital complementarities by pointing to the duality of human capital similarity to the population of firms and differentiation to rival firms as a motivation for mergers.

Second, I offer an in-depth analysis of the ways mergers affect the organizational boundaries

[7]The literature includes a large set of papers (e.g., Agrawal and Matsa, 2013; Tate and Yang, 2015; Graham et al., 2019; Baghai et al., 2016 among others)

[8]For evidence on the private equity literature, see Olsson and Tåg (2017) and Antoni et al. (2019).

of the firm. I relate post-merger compositional changes in human capital characteristics to different dimensions of technology adoption and organizational practices, by developing novel input-based measures that rely on textual analysis of occupational tasks. Previous literature has largely focused on physical assets, while examination of the labor effects of mergers has been largely limited to overall employment levels and average wages with limited evidence on post-merger changes in human capital composition due to data limitations. A notable exception is a contemporaneous paper by Ma et al. (2019) that relies on an occupation-level survey dataset in the U.S. to explore the impact of mergers on occupational employment and within-firm wage inequality. However, firm-level occupational information in the U.S. is based on sparse non-continuous survey information that prevents researchers from clearly measuring changes in firms' demand for specific human capital characteristics and distinguishing firm-level from individual-level employment decisions. By following the characteristics of employees who separate, join, and remain in firms in the period around the merger, I am able to isolate demand from supply-side considerations in firms' employment decisions, and directly measure the relation between mergers and the composition of the labor force across several important dimensions, particularly in a developing setting.

Third, I am able to draw inferences regarding the underlying motivations and point to technology adoption and knowledge transfers as sources of value creation in mergers. Pinning down the precise channels through which synergy gains emerge has been challenging due to data limitations. The disaggregate view of firms' labor force at the employee level allows me to test numerous theoretical predictions and uncover underlying economic mechanisms that drive post-merger compositional changes in human capital.

# 2 Institutional Setting

## 2.1 Merger Activity in Brazil

Brazil is a developing free-market economy that is currently the ninth largest economy in the world, having experienced significant growth from 2000 to 2012, with an average annual GDP growth exceeding 5%. In the early 2000s - following the successful implementation of the "Plano Real", privatizations of state-owned monopolies, and amidst a surge in commodity prices - Brazil transitioned into a stable platform for economic growth by implementing sound fiscal policies that resulted in a downward trend in inflation, an accumulation of foreign reserves, a reduction in public debt, and a modernization of the credit and capital markets. As a result of the fiscal, capital, and credit structural reforms, Brazil has been the subject of intense merger activity since the early 2000s. Appendix Figure A2 reports the number of announced and completed merger transactions (including minority-stake and partial acquisitions) that involve a Brazilian firm as a target, demonstrating the significant growth in the Brazilian merger market in the period from 2002 to 2014.

Except for certain regulated sectors (e.g., utilities) in which prior authorization by the sector-specific regulatory body is required, regulatory approval is not necessary to carry out an acquisition, unless the transaction triggers legal thresholds, in which case it is generally subject to approval by the Antitrust Authority (CADE).

### 2.2 Labor Regulation in Brazil

Labor regulations and employment protection, while ranking above average worldwide, are analogous to the ones observed in several developing and EU countries (Botero et al., 2004). Nevertheless, firing costs are relatively low in practice and there are no restrictions in labor-contract terminations without just cause. In addition, effective enforcement of labor regulations in Brazil is imperfect and costly. These labor market characteristics imply mergers are potentially associated with relatively low labor-adjustment costs despite the existence of relatively strict de jure labor market institutions.

The majority of labor contracts in the private sector are open-ended contracts, requiring compliance with legal termination procedures and severance compensation for employees dismissed without just cause. In addition, employers are subject to contributions to the Social Security System (INSS) and the Severance Savings Fund (FGTS). The employee is entitled to withdraw deposits from the FGTS account upon contract termination. Laid-off employees with at least six months of tenure are also eligible for unemployment insurance (UI) benefits after a 30-day waiting period with the potential UI duration being comparable to the one in the US.

## 3 Data Sources, Key Variables, and Sample Overview

### 3.1 Data Sources

#### Merger Data

Information on merger transactions that occurred in the period from 2004 to 2012 and involve a Brazilian firm as a target is obtained from Thomson's SDC. I focus on both private and public targets, and consider only completed transactions that involved the acquisition of a majority stake in the target firm and in which the effective date is within six months of the announcement date. I also eliminate partial acquisitions from the sample. Finally, I include both domestic and cross-border mergers in my analysis, and I associate foreign acquirers with the Brazilian entity that is used as the vehicle for the acquisition.

Firms based in Brazil are assigned an identification number from the Department of Federal Revenue (*Secretaria da Receita Federal do Brasil*), namely the National Registry of Legal Entities Number or CNPJ (*Cadastro Nacional da Pessoa Jurídica*). I use the names of the firms as reported in SDC to determine the CNPJ attached to firms involved in mergers. I also

manually scrutinize information on merger transactions, either provided by firms associated with the deal in the form of public announcements, or published in local government newspapers. Finally, for mergers where the approval of the Antitrust Authority was necessary, the respective reports were used to identify firms associated with the transaction.

**Employer-Employee Administrative Data (RAIS)**

Information on linked employer-employee relationships is obtained from RAIS, which has been collected by the Brazilian Ministry of Labor (Ministério de Trabalho e Emprego - MTE) since 1976. RAIS is a longitudinal administrative dataset that is compiled at an annual basis from information collected directly by formally-registered, public or private firms and includes comprehensive information on labor contracts that were active for at least part of the previous calendar year. Based on estimates of the Ministry of Labor, RAIS includes over 95% of formally employed individuals in Brazil.

The unit of observation in RAIS is a job entry that is identified by an employee-level identifier (PIS) and an establishment-level identifier (CNPJ) that enable me to track individuals over time and across firms. The firm-level identifier is extracted in a systematic manner by the establishment-level identifier and is used to identify firms in the RAIS data that have been involved in mergers using the information extracted from Thomson's SDC. Although the data are collected on an annual basis, I am able to restructure the data and perform my analysis using the month of the merger event by utilizing the information on the start and end month of the employer-employee relationship. I restrict my sample to the period from 2002 to 2017 so that employee-level information of at least two years before and five years after the merger is included.

RAIS includes information on the start and end date of the specific job entry, occupation type, wage level, and demographic characteristics. At the individual level, the available demographic characteristics are the gender, age, race and education level. At the establishment level, RAIS contains information on the geographical location and the sector in which an establishment operates. Importantly, RAIS contains information on the terminations of labor contracts, which allows me to disentangle involuntary from voluntary separations.[9] The occupation type is coded according to the Classificação Brasileira de Ocupações (CBO). RAIS contains a CBO code based on the 1994 classification and one based on the 2002 classification.

**Patent Data**

To create a measure of innovation activity, I scrape information on patents from the Brazil-

[9]Voluntary separations correspond to employee-induced terminations (e.g., resignations), whereas involuntary separations correspond to employer-induced terminations including layoffs and fixed-contract terminations without a subsequent renewal. In inferring separations, I exclude within-firm transfers, as well as retirements and reported deaths.

ian Patent Office. The Brazilian Patent Office contains comprehensive information on the population of patent applications submitted and subsequently approved from 1995 to 2020, and provides a direct search tool that allows me to extract the date of the patent submission and the identity of the firm to which the patent is assigned. In particular, I collect information on the number of patents for the period from 2002 to 2017. Then, I am able to match the information on firm-level innovation activity with the employer-employee dataset by exploiting the unique firm-level identifier (CNPJ) present in both databases.

### 3.2 Input-Based Measures of Organizational Changes

To examine the impact of mergers on the composition of human capital, I create input-based measures of organizational restructuring by relying on detailed information on individual characteristics and occupational tasks performed by employees as reported in RAIS. I hypothesize that post-merger changes in the production process are expected to manifest in meaningful changes in the type of employees and organizational tasks included in the boundaries of the firm after the merger. Specifically, I digitized the official descriptions of the 2,511 occupations from the Ministry of Labor, and employed textual analysis to extract information on the types of activities and tasks associated with each occupation. Then, I follow previous studies that have associated the task content of occupations with technological and organizational changes in the production process (e.g., Bresnahan et al., 2002; Autor et al., 2003; Bartel et al., 2007) and use the extracted occupational tasks to create input-based measures of firm-level restructuring. Using this strategy, I am able to document how mergers affect the organizational boundaries of the firm and draw inferences regarding the underlying motivations and sources of value creation in mergers.

#### Measures of Skill

I examine demand for high-skilled employees by leveraging information on employees' educational attainment as reported in RAIS. I define as high-skilled any employee that has some undergraduate education, and I estimate a firm's skill level using either the average years of education of its labor force or its share of high-skilled employees.

Alternatively, following the seminal work of Abowd et al. (1999) (hereafter AKM), I exploit the longitudinal employer-employee nature of the administrative dataset to estimate a wage regression that decomposes log-wages into a person and a firm fixed effect. The person fixed effect represents an individual's unobservable permanent human capital (e.g., ability), whereas the firm fixed effect has been associated in principle with firm-specific rents and productivity differences. Formally, the AKM methodology relies on the following log-linear specification of wages to quantify the relative importance of employer- and employee-specific components in determining wages:

$$w_{iJ(i,t)} = \theta_i + X'_{it}\beta + \psi_{J(i,t)} + \mu_t + \varepsilon_{it}, \quad (1)$$

where J(i, t) is the firm for which person i works at time t. The term $\theta_i$ represents the person fixed effect and captures the contribution of unobservable time-invariant individual characteristics on wages. $X'_{it}\beta$ captures the effect of employee-specific time-varying factors. I include quadratic, cubic, and quartic terms in experience[10] and their interactions with gender dummies. The term $\psi_{J(i,t)}$ represents the firm fixed effect and captures the effect of unobservable time-invariant firm characteristics on the wages of employees in firm j. Finally, $\mu_t$ captures unobservable heterogeneity across years and $\varepsilon_{it}$ is the error term.

I rely on the employee-level $\theta_i$ estimates as an alternative measure of employee skill, whereas I use the firm-level $\psi_{J(i,t)}$ estimates as a proxy for firm productivity.[11] I estimate person and firm fixed effects by employing a six-year rolling window approach in which I estimate separate AKM models in linked employer-employee panels for each cohort c of mergers, using only observations from year c-5 to year c. The primary reason behind the decision to focus only on the pre-merger period for the estimation of firm and employee fixed effects is to mitigate concerns of endogeneity from changes in wage premiums due to employee movements in the post-merger period. Appendix A provides additional information on the application of the AKM methodology and a discussion on its assumptions.

**Measures of Technology Adoption**

I create three distinct firm-level measures of technology adoption by using the task content of occupations assigned to employees in RAIS. I rely on the fact that technology is complementary to employees performing knowledge-intensive occupations and tends to displace employees performing routine tasks. The underlying assumption in using firm-level occupational shares to proxy for technological change is that investment in technology is associated with operational changes that require using employees who have the expertise and skills to perform the tasks associated with advancements in production. Additionally, changes in occupational shares are potentially better in capturing investment in technology and innovation compared to the lumpy nature of fixed capital investment and patents.

First, I develop a measure that captures investment in innovation activities based on the share of employees in occupations that involve innovation-intensive tasks. For this purpose, I use a set of keywords or combination of keywords that identify occupational tasks critical for the innovation process based on the technical documentation of the Survey of Innovation of

[10]Experience is defined as (Age - 2*Education Level - 4).

[11]The definition of high-productivity firms as high-wage firms is consistent with numerous recent models of frictional labor markets (e.g., Christensen et al., 2005), in which higher-productivity firms pay higher wages for equivalent workers, and has been extensively used in empirical studies (e.g., Serafinelli, 2019; Alvarez et al., 2018).

Brazilian firms (PINTEC).[12] The set of keywords is reported in Panel A of Appendix Table A1 and broadly describes occupational tasks that capture product and process innovation (e.g., "Develop Products"; "Develop Research"; "Improve Systems"). I alternatively consider a direct measure of technology adoption by using the share of employees in professional occupations (e.g., scientists, engineers) and the share of blue-collar employees, given that technological change tends to be followed by substitution of low-skilled labor.[13]

Second, I create a measure that captures the adoption of labor-saving technologies using the share of employees performing routine occupational tasks. For this purpose, I use information on occupational routine intensity provided by Autor and Dorn (2013). Specifically, Autor and Dorn (2013) create an index that measures occupational routine task intensity (RTI) based on the types of tasks (abstract, manual, routine) performed by each occupation. Following the approach developed by Muendler et al. (2004), occupational codes in RAIS are mapped to the International Standard Classification of Occupations (ISCO) which is then used to assign RTI scores. I consider an individual to perform a routine occupation if the RTI score is positive and a non-routine occupation if the RTI score is negative.[14]

Finally, I develop measures that capture investment in information technology and adoption of IT-enabled organizational change (Bresnahan et al., 2002; Bartel et al., 2007). To create a direct firm-level measure of investment in IT, I identify employees assigned to IT occupations (e.g., software engineers, database administrators).[15] In addition, Bresnahan et al. (2002) argue that IT adoption is followed by complementary organizational changes that increase the demand for occupational tasks that involve interaction with computers and data processing and analysis. Therefore, I follow the previous literature (e.g., Agrawal and Tambe, 2016; Antoni et al., 2019) and use the set of keywords reported in Panel B of Appendix Table A1 to identify IT-enabled occupations. Employees in IT-enabled occupations range from clerical support employees to supply chain managers and machine operators.

**Measures of Occupational Overlap**

I create two variables of occupational overlap between firm pairs. The first variable is a continuous measure of pairwise proximity between any two firms in the occupational space that accounts for the number of employees assigned to a specific occupation. Specifically, I use firm-level occupational distributions of employees to construct a measure of occupational

[12] See Bustos et al. (2019) for an industry-level application of this methodology to explore the impact of structural transformation on industrial development and productivity growth. The industry-level measure has a positive correlation with R&D expenditure per worker.

[13] Employees in professional occupations are identified using the one-digit CBO 2002 code 2. Blue-collar employees are identified using the one-digit CBO 2002 codes from 6 to 9.

[14] Alternatively, an occupation is defined to be routine-intensive if the occupation is in the top employment-weighted third of routine intensity in a given year. The results are qualitatively and quantitatively unchanged regardless of the definition of routine workers (the correlation of the routine variables is 0.89).

[15] The CBO 2002 four-digit codes that identify IT occupations are 1236, 1425, 2122, 2123, 2124, 3171, 3172.

proximity of any two firms $T$ and $A$ as the scalar product of the firms' occupational profile vectors divided by the product of the vectors' lengths:[16]

$$\text{Occupational Proximity}_{TA} = \frac{O_T O'_A}{\sqrt{O_T O'_T}\sqrt{O_A O'_A}} \tag{2}$$

The *Occupational Proximity* measure is bounded between zero and one with one capturing merger pairs with identical occupational profiles.

The second variable is based only on the occupational profiles of the acquirer or the target firm and is equal to the share of distinct occupations that are present in both the acquirer and the target firm at the time of the transaction over the total number of distinct occupations of the acquirer or the target firm respectively.

### 3.3 Sample Overview

I begin with 2,926 merger transactions from Thomson's SDC from 2004 to 2012 that involve a majority-stake acquisition, and I use the manually collected firm-level identifiers to determine firms involved in merger activity in RAIS. To identify firms that are economically active, I only include target firms with at least five employees in RAIS at the year prior to the merger. My sample includes 2,104 merger transactions involving 2,430 target firms.[17]

Figure 1 provides information on the annual number of merger transactions from 2004 to 2012, calculated from the SDC-RAIS intersection, and highlights the intensity of merger activity in Brazil during the period under study. Notice that, although SDC is considered the primary source of information on mergers, a potential selection exists in reporting ownership changes towards larger firms.

Figure 2 provides information on the classification of target firms into size categories, using total employment at the time of the transaction as a measure of size, along with size percentages for the population of firms present in RAIS that have never been involved in merger activity. As reported in Figure 2, the distribution of target firms is skewed to the right relative to the population of firms. In particular, around 93% of target firms have at least 10 employees versus only 20% in the population of firms.

Panel A of Table 1 provides information on the characteristics of merger transactions. Notice only 3% of mergers in Brazil involve target firms that are publicly listed, whereas, consistent with the increased interest from foreign investors in the fast-growing Brazilian economy during the period of study, around 42% of mergers are cross-border. Furthermore, Panel B

[16] See Lee et al. (2018) for an application of this methodology using industry-level occupational profiles and Compustat-segment data to examine the relation between human capital complementarities and the merger incidence.

[17] There are transactions that involve the acquisition of more than one firms.

of Table 1 reports aggregate estimates for the shares of merger transactions by sector showing that merger activity has been concentrated in the services and manufacturing sectors.[18]

Finally, Panel C of Table 1 provides evidence that acquirers actively restructure target firms' labor inputs by exploring within-firm reallocation rates of employees in target establishments that were subsequently disposed. Column (1) reports establishment disposal rates and shows that a large set of acquired establishments is disposed in the five-year period after the merger in line with evidence for the post-merger restructuring process of real assets in the US (Maksimovic et al., 2011). In particular, acquirers dispose on average 56.5% of the acquired establishments that account for around 52.6% of total employment. However, as illustrated in Column (3), acquirers actively reallocate 56.4% of employees suggesting human capital considerations play an important role in post-merger restructuring decisions.

# 4 Ex Ante Selection Effects in the Merger Decision

## 4.1 Estimation Strategy

To examine the relation between firm-level human capital characteristics and the likelihood that a firm becomes an acquirer or a target firm, I estimate the following linear probability specification:

$$\begin{aligned}\text{Merger Incidence}_{ims,t} = \alpha_{s,t} + \alpha_m + \beta_1 \text{Firm Human Capital Characteristics}_{ims,t-1} + \\ + \beta_2 \text{Firm Characteristics}_{ims,t-1} + \varepsilon_{imst}\end{aligned} \tag{3}$$

The dependent variable is an indicator variable that is equal to one if firm $i$ is involved in the merger transaction $m$ at the calendar year $t$, and zero otherwise. I employ separate specifications to estimate the likelihood that a firm is engaged in a merger as an acquirer or as a target firm in any given year, conditional on not being involved in a transaction the year before. The specification includes time-varying lagged firm-level human capital characteristics as independent variables to capture different dimensions of a firm's labor composition. In particular, I use the average years of education of a firm's labor force as a measure of skill intensity, the average routine task intensity as a measure of a firm's adoption of labor-saving technologies, the share of innovation-intensive and blue-collar employees as a measure of a firm's technological advancement and innovation activities, and measures of broad and within-sector occupational proximity. *Firm Characteristics* is a vector of firm-level controls that includes the logarithm of employment and average monthly employee wage at the year prior to the merger. Finally, the specification includes a combination of year, industry and transaction fixed effects.

I use two different set of control firms as potential merger participants. First, I use the population of firms that are never involved in a merger transaction over the period under

[18]The aggregation of merger transactions by sector is based on the sector classification from Dix-Carneiro (2014).

study, are present in RAIS for at least four years, and have at least five employees in a given year. Second, I follow Bena and Li (2014) and create a set of control firms for acquirers and target firms by sector and size that are never involved in a merger transaction over the period under study. In particular, I select up to five control firms that operate in the same two-digit sector[19] and have the closest propensity score using a linear probability model that includes a quadratic in employment and in total payroll at the year prior to the merger. As a result, the matching process accounts for clustering both in terms of time and sector.

To investigate the role of occupational overlap in affecting the merger incidence, I estimate the following linear probability specification:

$$\begin{aligned}\text{Merger Incidence}_{ijm,t} = \alpha_m + \beta_1 \text{Occupational Overlap}_{ijm,t-1} + \\ + \beta_2 \Delta \text{Firm Human Capital Characteristics}_{ijm,t-1} + \varepsilon_{ijmt}\end{aligned} \tag{4}$$

The dependent variable is an indicator variable that is equal to one if firm $i$ is involved in the merger transaction $m$ with firm $j$ at calendar year $t$, and zero otherwise. *Occupational Overlap* includes the set of variables that capture the degree of occupational relatedness as described in Section 3.2. Additionally, the specification considers variables that capture the distance (in absolute values) between firm pairs in terms of skill and routine task intensity. Finally, the specification includes transaction fixed effects. The sample for the analysis is formed using pairs of firms based on the sector- and size-matched control groups created in the previous step. In particular, I pair acquirers with up to five of the closest matches to the target firm based on sector and size, and target firms with up to five of the closest matches to the acquirer based on sector and size.

### 4.2 Which Firms Merge?

Table 2 explores the patterns of selection by providing descriptive statistics for firms involved in mergers and control firms from the sector- and size-matched sample. Three findings emerge from the table. First, as shown in Panels A and B, positive selection exists in the sense that both acquirers and target firms have a significantly larger share of high-skilled and innovation-intensive employees and a lower share of blue-collar employees relative to the set of control firms by sector and size. One notable exception though is that target firms display a larger degree of routine task intensity relative to the control group. Second, consistent with a "high-buys-low" pattern (Jovanovic and Rousseau, 2002), acquirers are significantly larger, have a higher share of high-skilled employees and a lower level of routine task intensity compared to target firms. However, they are similar in terms of innovation-intensive and blue-collar shares. Third, Panel C provides evidence that occupational overlap is significantly higher between acquirers and target firms. In particular, the occupational proximity measure between target firms and acquirers is, on average, 0.35 and overlap is

[19] If there is no control firm within a given two-digit sector, I repeat the matching process using the one-digit sector, or the sector classification from Dix-Carneiro (2014).

generally higher in target firms than acquirers. Furthermore, the extent of proximity in terms of skill and routine intensity is larger between acquirers and target firms highlighting the role of asset complementarities in driving merger activity.

I next turn to a systematic analysis of the relation between human capital characteristics and selection into engaging in merger activity by estimating Equation (3) separately for target firms and acquirers. The results are reported in Columns (1) to (6) of Table 3. Columns (1) and (2) report the estimated coefficients for target firms using the population of firms and the set of sector- and size-matched firms as control group respectively. I find firms with higher skill levels and a larger share of innovation-intensive employees are more likely to become target firms. Across specifications and different samples, the coefficients on skill and innovation-intensive share are significant at the 1% level. In terms of magnitudes, the estimates in Column (2) imply that a one-standard-deviation increase in skill and innovation intensity increases the probability of being acquired by 1.07 and 1.28 percentage points respectively. Notice that the coefficient on routine task intensity turns positive and significant in Column (2) indicating that target firms adopted a lower level of automation relative to sector- and size-matched peer firms at the year prior to the merger despite exhibiting no differences in routine task intensity compared to the average firm in the population.

Columns (4) and (5) present the coefficient estimates for acquirers using the population of firms and the set of sector- and size-matched firms as control group respectively. The results suggest a positive and statistically significant relation exists between the level of skill and the probability of becoming an acquirer across the different sets of control firms, while the degree of innovation intensity positively predicts the incidence of becoming an acquirer (albeit statistically insignificant when using the sector- and size-matched sample). However, contrary to the findings for target firms, I find firms with a lower degree of routine task intensity are more likely to become acquirers.

Overall, firms with a higher level of skill and innovation intensity are more likely to be involved in merger activity, consistent with positive selection in terms of human capital composition. However, the degree of routine task intensity has different implications regarding selection into becoming an acquirer or a target firm with acquirers exhibiting a higher level of adoption of labor-saving technology. Given that the analysis focuses on an emerging economy with a large part of mergers originating from developed countries, the findings on positive selection are consistent with Bena and Li (2014) for innovation characteristics and Guadalupe et al. (2012) for the relation between foreign ownership and initial productivity.

I next examine the relation between occupational overlap and the transaction incidence. Columns (3) and (6) report estimates from Equation (3) using the sector- and size-matched sample as the control group for target firms and acquirers respectively. I consider two ex ante

measures of occupational overlap estimated at the year prior to the merger using Equation (2). The first measure proxies for ex ante broad human capital relatedness by estimating the average degree of occupational proximity of a firm with the population of firms, whereas the second measure captures ex ante human capital differentiation from firms within a sector by estimating the average occupational proximity only with the set of firms in the sector- and size-matched sample. The results suggest that a firm is more likely to be an acquirer or a target if the broad occupational proximity is high, pointing to the ability of merging firms to both exploit cost synergies and skillfully manage the acquired human capital. However, firms with high occupational proximity with rival firms are less likely to restructure either as targets or as acquirers, highlighting the importance of human capital differentiation as a motivation of mergers.

Furthermore, Columns (7) and (8) explore the relation between occupational overlap and the formation of merger pairs by estimating Equation (4) with the sector- and size-matched sample as the control group. I find a positive and statistically significant relation between any of the measures of pairwise occupational overlap and the likelihood of a merger pair formation. These results extend and corroborate evidence in Lee et al. (2018) that human capital complementarities motivate mergers by leveraging detailed administrative employee-level occupational profiles to create measures of occupational overlap. Additionally, consistent with the "like-buys-like" theoretical argument in Rhodes-Kropf and Robinson (2008), merger pairs are more likely to be formed between firms that are closer in terms of skill and routine intensity even within a sector and accounting for size differences. Taken together, my findings provide strong support that underlying human capital synergies between firms are important determinants of mergers.

# 5 Post-Merger Treatment Effects

Having established the presence of selection effects of human capital characteristics on merger participants, I next characterize the extent and direction of post-merger labor restructuring and shed light on potential mechanisms behind the observed compositional changes.

## 5.1 Estimation Strategy

### 5.1.1 Treatment and Control Group

For the research design, I follow previous studies in the merger literature (e.g., Maksimovic et al., 2011; Li, 2013), and hypothesize that mergers represent a shock to target firms' employees. Thus, I use the target firm as the unit of analysis. To analyze post-merger treatment effects on the reorganization of the labor force, the primary econometric challenge is selection bias reflecting the non-random distribution of merger activity across industries and firm characteristics. As demonstrated in the previous section, target firms are different

from firms that are not involved in mergers with target firms being disproportionally larger and having different human capital compositions. To address the potential selection issue that arises from selection based on observable characteristics, I use a matching estimator approach and identify a set of counterfactual firms based on a set of interactions among observable firm characteristics. This matching strategy has been the standard approach in the literature in combination with an event-study specification (Davis et al., 2014; Olsson and Tåg, 2017; Graham et al., 2019).

Specifically, for each firm acquired in year t, I select a potential counterfactual firm that (i) has never been involved in merger activity either as a target or as an acquirer, (ii) operates in the same two-digit sector,[20] (iii) is registered as the same business type as the target firm, (iv) has the same multi-establishment status, and (v) is in the same size and total payroll decile at the year prior to the merger event as the target firm. I then select the firm with the closest propensity score, using a linear probability model that includes a quadratic in employment and total payroll, and the shares of high-skilled and routine employees.

Table A3 in the Appendix presents employee-level descriptive statistics for treated and control firms at the year prior to the transaction. Consistent with the matching procedure finding comparable counterfactuals, the human capital composition is balanced between the treated and control group in terms of individual characteristics (e.g., education, age, tenure)[21] and occupational tasks (e.g., innovation and routine intensity).

### 5.1.2 Empirical Specifications

To examine the impact of mergers on the composition of labor, I employ a difference-in-differences specification around the timing of the merger by comparing changes in human capital for target firms relative to the set of counterfactual firms, controlling for a battery of fixed effects and individual characteristics. I restrict my focus to a two-year period before and a five-year period after the merger. In selecting the timing of the merger, I use the merger announcement date provided by SDC. Specifically, the granularity of the RAIS data allows me to use the year-month of the merger announcement date and construct leads and lags at the annual level around the precise time of the transaction. As a result, I circumvent the problem of the treatment group being partially treated at the time of the event.

For the firm-level analysis, I estimate the following event-study specification:

$$Y_{it} = \alpha_i + \alpha_t + \gamma Post_p + \delta Post_p \times I_i^{Treated} + \varepsilon_{it} \tag{5}$$

$Y_{it}$ is an outcome variable for firm $i$ in calendar year $t$. The index $p$ corresponds to normalized

[20] If there is no control firm within a given two-digit sector, I repeat the matching process using the one-digit sector, or the sector classification from Dix-Carneiro (2014).

[21] The only exception is gender with control firms employing a lower share of women.

time expressed in years relative to the merger and ranges from $-2$ to $+5$. $Post_p$ is an indicator variable equal to one for the five-year period after the merger, and equal to zero for the two-year period prior to the merger. The variable $I_i^{Treated}$ is an indicator variable equal to one for target firms at any point in time, and equal to zero for counterfactual firms that have never been involved in a merger transaction either as targets or acquirers during the period under study. Finally, the specification incorporates firm and year fixed effects to absorb unobservable time-invariant differences across firms and years. The coefficient of interest, $\delta$, captures the average difference in the outcome variable between treated and control firms in the five-year period after the merger relative to the two-year period prior to the merger event. The standard errors are clustered at the transaction level so as to account for correlation between the different target firms involved in a merger transaction.[22]

I also extend the previous specification to explore the dynamic effects of mergers:

$$Y_{it} = \alpha_i + \alpha_t + \sum_{p=-2}^{p=+5} \lambda_p d_{it}(p) + \sum_{p=-3}^{p=+5} \delta_p d_{it}(p) \times I_i^{Treated} + \varepsilon_{it} \tag{6}$$

The indicator variable $d_{it}(p)$ is equal to one if $d_{it}(p) = p$ and is used to identify leads and lags around the time of the transaction.

Finally, to examine post-merger changes in a firm's demand for specific employee characteristics and occupational tasks, the individual is used as the unit of analysis and the event-study specification has the following form:

$$\begin{aligned} Y_{ijt} = \alpha_i + \alpha_t + \gamma Post_p + \beta I_j^C + \delta Post_p \times I_j^{Treated} + \zeta Post_p \times I_j^C + \\ + \eta I_j^{Treated} \times I_j^C + \mu Post_p \times_j^{Treated} \times I_j^C + X_j'\theta + \varepsilon_{ijt} \end{aligned} \tag{7}$$

$Y_{ijt}$ is an outcome variable for employee $j$ in calendar year $t$ employed in firm $i$. The variable $I_j^{Treated}$ is an indicator variable equal to one for individuals employed in a target firm at any point in time, and equal to zero for employees in counterfactual firms that have never been involved in a merger either as target firms or acquirers during the period under study. $X_j'$ is a vector of individual controls that includes age, gender and tenure. The coefficient of interest $\mu$ measures the average difference in outcome variables between groups of employees distinguished by the characteristic $C$ in treated firms relative to employees with the same characteristic in control firms and relative to employees that are not part of this group.

### 5.1.3 Identifying Assumptions

The identifying assumptions that allow a plausibly causal interpretation of the estimated treatment effect in a difference-in-differences specification are the parallel-trends assumption and the stable unit treatment value assumption (SUTVA). The parallel-trends assumption requires that the outcomes under study for the treated and control group would have followed

[22] The coefficient estimates for the term $I_i^{Treated}$ are absorbed by the firm fixed effect.

parallel trends in the absence of treatment. To assess the plausibility of this assumption, I compare the trajectory of outcome variables in the pre-merger period in Section 5.2. Importantly, because the matching estimator approach is based on observable characteristics that do not include pre-merger trends of outcome variables, the existence of parallel trends in the pre-merger period would indicate pre-merger shocks have affected treated and control workers in a similar manner.

The SUTVA requires that mergers have no general equilibrium effects on the outcomes of counterfactual firms. However, given that the set of control firms has been selected using a broad definition of sector which contains a sufficient number of firms, the firms included in the sample are unlikely to constitute a large fraction of the sector.[23]

Nevertheless, since the matching estimator approach is based on observable characteristics to identify a set of counterfactual firms, unobserved factors or shocks are likely to be responsible for generating a difference in post-merger trends between labor-related outcomes in treated and control firms. For example, if positive shocks induce merger activity, changes in the composition of human capital that reflect technological adoption may materialize in the post-merger period even in the absence of the direct impact of the merger. While the fact that compositional changes occur precisely at the time of the merger is reassuring, the empirical specification employs a battery of time-varying fixed effects to isolate the source of identifying variation and tests the robustness of the estimated magnitudes to various identifying assumptions. Notice, however, that, because of the likelihood of selection in unobservable factors, I refrain from drawing causal interpretations about the empirical findings. Yet, exploring the post-merger reorganization of target firms' labor force in firms and reporting the estimated correlations increase our understanding of the potential sources of value creation in mergers and the readjustment of organizational boundaries.[24]

### 5.2 Mergers and Skill Composition

I first examine the impact of mergers on skill intensity. Prior literature has highlighted the role of mergers as vehicles for improving operating performance, increasing the productivity of inputs, and facilitating growth (e.g., Lichtenberg et al., 1987; Maksimovic and Phillips, 2001; Li, 2013). I hypothesize that post-merger operational and organizational changes in the production process are expected to manifest in meaningful changes in the skill composition of employees included in the boundaries of the firm in the post-merger period.

Theoretically, there are numerous non-mutually exclusive mechanisms through which mergers are expected to affect the skill composition of target firms. First, neoclassical merger

[23]In addition, the direction and magnitude of the baseline results remain unchanged when the set of counterfactual firms includes only firms that are not in the same sector as the treated firms.

[24]In unreported results, I augment the empirical analysis using a limited number of withdrawn mergers (67) by documenting that there are no compositional effects. However, I am unable to find information on the reasons behind the bid withdrawal for 40% of the cases.

theories are based on the view that mergers are an efficient response to regime shifts by value-maximizing managers (e.g., Gort, 1969; Mitchell and Mulherin, 1996). As such, mergers reallocate control of productive assets to more efficient uses and better managers. Central to neoclassical theories, the q-theory of mergers (Jovanovic and Rousseau, 2002) relies on the premise that better managers and better projects are complements and mergers are expected to be followed by technological advancement (Jovanovic and Rousseau, 2008). To the extent that technological change and high-skilled labor are complements, neoclassical theories predict an increase in skill intensity. Similarly, agency theories of mergers may predict an increase in target firms' skill intensity if mergers replace inefficient managers that are, for example, resistant to technological change (e.g., Jensen and Ruback, 1983). Finally, mergers have been associated with the resolution of financial constraints (e.g., Almeida et al., 2011; Erel et al., 2015), implying that post-merger availability of financial resources potentially allows previously financially-constrained target firms to attract high-skilled employees by offering better compensation packages.

To proxy for skill, I use information on employees' years of education and the person fixed effects estimates as described in Section 3.2.[25] The analysis is at the employee level and is based on the following specification which is a simplified version of Equation (7):

$$Y_{ijt} = \alpha_i + \alpha_t + \gamma Post_p + \delta Post_p \times I_j^{Treated} + X_j^{'}\theta + \varepsilon_{ijt} \tag{8}$$

The coefficient of interest, $\delta$, captures the average difference in the level of skill between treated and control employees in the five-year period after the merger relative to the two-year period before. The estimated coefficients are reported in Panel A of Table 4. Columns (1) and (4) provide evidence that mergers are associated with an increase in employees' level of skill. The magnitudes of the estimates correspond to statistically and economically significant increases in the years of education and the person fixed effect of 0.14 years (or 4.2% of a standard-deviation increase) and 0.8 log points (or 2.9% of a standard-deviation increase) respectively. Additionally, in Columns (3) and (6) I find the increase in the level of skill emerges from post-merger hiring of more skilled employees, while in Columns (2) and (5), I find no differences in skill for employees that involuntarily exit target firms.

Panel B of Table 4 examines changes in target firms' labor demand for high-skilled employees from estimating Equation (7). The dependent variables are employee-specific indicator variables that measure the incidence of involuntary separation and hiring. An important advantage of RAIS is that it contains detailed information on terminations of employment contracts. This allows me to precisely identify involuntary separations and disentangle demand- and supply-side factors that affect the employment decisions of firms. Columns (1) and (2) report estimates based on educational attainment, whereas Columns (3) and (4) based on

[25]The correlation between education and the person fixed effect is 0.69.

the person fixed effects to identify high-skilled employees. Specifically, I use the top quartile to classify employees into high-skilled using the person fixed effects.

In line with the disproportionate importance of high-skilled employees for firm productivity (Abowd et al., 2005), the estimates in Panel B indicate a post-merger increase in demand for high-skilled employees. For example, Column (1) reports a 3.4-percentage-point (or 25% relative to the sample mean) statistically and economically significant decline in the incidence of involuntary separation for high-skilled employees in target firms relative to low-skilled employees and to employees in control firms. Additionally, Column (2) suggests the decline in separations is accompanied by a significant increase of 6.6 percentage points (or 22% relative to the sample mean) in the hiring incidence.

To examine the evolution of skill composition, in Figure 3, I plot the $\delta_p$ estimates from Equation (6) along with 95% confidence intervals using the share of high-skilled employees as the dependent variable. The vertical line represents the timing of the merger transaction, that is the latest period prior to the merger. In support of the parallel-trends assumption, no statistically significant differences exist in the pre-merger trajectory of skill between treated and control firms, implying the matching process is potentially effective in mitigating concerns related to selection bias. However, relative to the control group, target firms experience a statistically significant and persistent post-merger increase in skill intensity. In particular, target firms' share of high-skilled employees increased instantly in the year of the merger and never reverted in the period under study remaining at a higher level relative to the share prior to the merger. The magnitudes of the coefficient estimates from using Equation (8) are reported in Column (3) of the Appendix Table A4 and suggest target firms experienced, on average, a long-term increase of 1.9 percentage points in the share of high-skilled employment that corresponds to a 8.6% increase relative to the sample mean.

### 5.3 Mergers and Technology Adoption

In this section, I turn to the hypothesis that mergers are associated with operational and organizational changes that foster innovation and technology adoption. Previous literature has highlighted that mergers emerge as a mechanism that advances technology and raises the innovation output (Bena and Li, 2014). As a result, target firms are able to implement new technologies at a faster pace. To investigate the role of technology adoption in shaping the human capital composition in the post-merger period, I distinguish between different facets of technological change that have different implications for the composition of human capital. An important feature of this paper's research design is the use of detailed information on occupational tasks performed by employees to develop input-based measures that allow me to proxy for different dimensions of investment in technology and innovation. The underlying assumption is that post-merger technological change requires employees who have the expertise and skills to perform the tasks associated with advancements in technology,

thus leading to compositional changes in target firms' human capital.

First, I consider the role of the skill-biased technological change hypothesis that relies on the premise that technology adoption is followed by a rise in the demand for high-skilled labor (Katz and Autor, 1999). To the extent that the observed increase in skill composition reflects changes in technological efficiency that increases skill requirements, I should observe broader post-merger compositional shifts in the direction of knowledge-intensive occupational tasks. However, if this increase only reflects replacement of the existing labor force with more skilled employees without any subsequent occupational shifts, skill-biased technological change is unlikely to be a byproduct of mergers.

For this purpose, I examine post-merger labor demand for employees in knowledge-intensive occupations, that is occupations for which the minimum level of educational attainment required is a college degree. Information on the minimum educational attainment by occupation is provided by the Brazilian Ministry of Labor. The coefficient estimates from using Equation (7) are reported in Columns (5) and (6) of Panel B of Table 4 and provide empirical support for the skill-biased technological change hypothesis. I find mergers are followed by a 2.9-percentage-point decline in the likelihood of involuntary separation and a concurrent 5.4-percentage-point increase in hiring for employees in knowledge-intensive occupations. Figure 4 shows the dynamic effects of mergers on the share of employees in knowledge-intensive occupations, suggesting the existence of a persistent long-term post-merger increase of 2.9 percentage points.

Alternatively, Columns (3) to (6) of Panel A of Table 5 report coefficient estimates for different occupational groups that are expected to be affected by technology adoption. Specifically, Columns (3) and (4) focus on labor demand for professional occupations (e.g., engineers and scientists), whereas Columns (5) and (6) provide estimates for employees in blue-collar occupations. To the extent that mergers induce an increase in demand for occupational roles with higher skill requirements, target firms are expected to substitute blue-collar employees with employees in professional occupations. The results provide support that, indeed, target firms replace blue-collar employees with professional employees by increasing involuntary separations for blue-collar employees and hiring for professional employees.

I next consider the role of mergers in fostering innovation. The recent literature portrays mergers as vehicles that increase the innovation efficiency of target firms. For example, Bena and Li (2014) provide evidence that mergers occur due to technology considerations and increase innovation output, while Guadalupe et al. (2012) demonstrate that foreign ownership is followed by organizational practices that generate productivity-enhancing innovation. Therefore, I hypothesize that if mergers encourage innovation, the composition of the labor force is expected to shift in a direction that reflects an increase in the demand for innovation-intensive occupational tasks. To test this hypothesis, I employ the input-based

measure of innovation intensity described in Section 3.2 that identifies occupational roles that engage in innovation activities.

The results from estimating Equation (7) are reported in Columns (1) and (2) of Panel A of Table 5. Column (1) examines involuntary separations and demonstrates that there is a statistically and economically significant post-merger decline of two percentage points (or 14% relative to the sample mean) for employees in innovation-intensive occupations that is accompanied by a significant increase of 2.2 percentage points (or 7.6% relative to the sample mean) in hiring as reported in Column (2). Figure 5 plots the trajectory of the share of innovation-intensive employees and shows a persistent 0.7-percentage-point increase in the post-merger period that corresponds to a 8.2% increase relative to the sample mean. Taken together, my findings provide strong empirical support that mergers are associated with skill-intensive shifts in the demand for human capital directed at knowledge- and innovation-intensive occupational tasks.

I next examine adoption of labor-saving technologies. Recent literature has highlighted the role of technology-driven automation in displacing employees that perform routine occupational tasks (e.g., Autor and Dorn, 2013). There are multiple mechanisms that predict post-merger adoption of routine-biased technological change. For example, mergers may foster automation by replacing inefficient or entrenched managers that are resistant to the adoption of labor-saving technologies (Jensen and Ruback, 1983; Bertrand and Mullainathan, 2003) or ally with employees (Pagano and Volpin, 2005). Alternatively, post-merger economies of scale may decrease the fixed costs of investing in automation. Therefore, I hypothesize that adoption of labor-saving technologies is expected to manifest in the labor composition of target firms by replacing employees that perform repetitive routine tasks. For this purpose, I use the input-based measures of routine task intensity as described in Section 3.2.

The results are presented in Columns (1) and (2) of Panel B of Table 5 and document a post-merger decline in demand for employees that perform routine occupational tasks. I find mergers are associated with a statistically significant 2.7-percentage-point increase in the probability of involuntary separation and a 2.9-percentage-point decline in the hiring incidence of routine employees. Figure 6 examines the evolution and the timing of changes in the share of routine employees and provides evidence of a long-term decline of 2.1 percentage points that predominantly occurs during the first year of the merger.

Finally, the literature on organizational economics has highlighted the role of investment in information technology and the implementation of IT-based organizational practices in explaining skill-intensive shifts in labor demand and firm-level operational improvements (Bresnahan et al., 2002; Bartel et al., 2007). Therefore, I hypothesize that a channel through which mergers affect labor composition is by increasing investment in IT and imposing operational practices that are complementary to IT-enabled occupational tasks. To investigate

this hypothesis, I use measures that capture direct investment in IT and the adoption of IT-enabled organizational practices from Section 3.2. The results are presented in Columns (3) to (6) of Panel B of Table 5. In Columns (3) and (4) I focus on IT occupations and find mergers are associated with a statistically significant 3.4-percentage-point decline in the probability of involuntary separation and a 4.1-percentage-point increase in the hiring incidence of IT employees. Similarly, the estimates in Columns (5) and (6) suggest target firms exhibit an increase in demand for occupations that perform IT-enabled tasks.

Overall, these findings provide direct support for the role of mergers in imposing compositional shifts in target firms' human capital in a direction that is consistent with technological upgrade, increase in the innovation intensity and adoption of labor-saving technologies. Notice that, while the granularity of occupational data allows me to distinguish between different dimensions of post-merger technology adoption, these technological changes are intertwined. For example, investment in information technology alters the production process in a direction that increases skill requirements and the importance of innovative and non-routine tasks.

### 5.4 Mergers and Organizational Streamlining

In this section, I explore the relationship between mergers and two important dimensions of organizational change. First, I focus on the role of occupational overlap in explaining labor restructuring decisions in the post-merger period. Synergy gains have long been considered an important driver of mergers (e.g., Andrade et al., 2001; Devos et al., 2009). An important theoretical mechanism though which synergies materialize is the existence of asset complementarities (Rhodes-Kropf and Robinson, 2008). For example, Hoberg and Phillips (2010) show that product market complementarities in mergers are followed by better operating performance. Sheen (2014) provides evidence that mergers between product market competitors generate efficiency gains through cost savings and operational consolidation. Bena and Li (2014) highlight the importance of technological overlap in motivating mergers, while Lee et al. (2018) combine information on the distribution of occupations at the industry level with segment data from Compustat to demonstrate empirically that human capital complementarities motivate mergers for firms that operate in unrelated industries or product markets. As a result, I expect acquirers in mergers with high degree of occupational overlap to exploit economies of scale and economize on labor costs by eliminating employees in overlapping occupations.

To test this hypothesis, I use the measures of occupational overlap from Section 3.2 for the subsample of merger transactions where I have information on occupational profiles for both the acquirer and the target firm. The results from estimating Equation (7) are presented in Panel A of Table 6. Columns (1) and (2) report estimates from using a merger-level binary measure of occupational overlap where I classify mergers into high- and low-overlap based

on the median value of the continuous measure of pairwise occupational proximity between the acquirer and the target firm. Alternatively, Columns (3) to (6) present results using an employee-level measure of occupational overlap where I assign an indicator variable equal to one for target firms' employees who perform an occupation that overlaps with the acquirer. The variables of interest are the likelihood of involuntary separation and hiring.

Overall, I find occupational overlap to be an important driver of post-merger involuntary separations pointing to cost synergies and operational consolidation as potential sources of efficiency gains. The magnitudes of the coefficient estimates in Column (1) suggest target firms' employees in mergers with a high degree of occupational proximity experience a 5.2-percentage-point increase in the probability of involuntary separation. The effect is statistically significant at the 1% level and the economic magnitude represents a 33% increase relative to the sample mean. Turning to the employee-level measure, Column (3) shows that employees in occupations that overlap with the acquirer experience a post-merger increase of two percentage points in the incidence of involuntary separation.

Additionally, Columns (5) and (6) report estimates for the employee-level measure for focused and diversifying mergers. To classify mergers into focused and diversifying, I follow Tate and Yang (2016) and identify a merger as diversifying if there is no overlap in the industries in which acquirers' and target firms' establishments operate at the time of the transaction. I find that occupational overlap increases the incidence of involuntary separation only in focused mergers, while there is no statistically significant effect in diversifying mergers. This evidence suggests occupational overlap enables acquirers in focused mergers to generate operational synergies from cost savings and occupational redundancies in duplicate operations. Finally, Appendix Table A5 reports estimates from repeating the previous analysis for employees in acquirers and shows that occupational overlap has no significant effect on acquirers' employees. This finding is consistent with asymmetric information regarding employee-specific productivity playing an important role in the process of screening and retaining overlapping employees in the post-merger period.

In a second step of the analysis, I examine post-merger changes in decision rights and demand for clerical support employees. Prior research has pointed to the alleviation of agency frictions as a source of value creation in mergers by disciplining poorly-performing managers (e.g., Manne, 1965; Martin and McConnell, 1991) or by replacing entrenched managers that follow a "quiet life" (Bertrand and Mullainathan, 2003) and ally with the employees (Pagano and Volpin, 2005). In this case, the observed compositional changes may be the the outcome of replacing managers that are resistant to the adoption of organizational and technological changes. Lichtenberg and Siegel (1990) also provide evidence that ownership changes are followed by substantial reductions in administrative overhead. As a result, I expect mergers to be followed by the replacement of incumbent management and a leaner workforce.

To examine post-merger changes in management, I focus on both (high-level) managers (e.g., CEOs, CFOs) and supervisors. I identify high-level managers directly using the occupational codes assigned to employees in RAIS.[26] To identify employees that act as supervisors, I use a textual analysis approach based on the detailed description of tasks performed by occupations. The set of keywords is reported in Appendix Table A2 and describes tasks that capture supervision, monitoring and coordination of employees. Supervisors span different levels of skill ranging from professional to blue-collar occupations. To identify clerical support employees, I use the occupational codes in RAIS.[27]

The results from estimating Equation (7) using the incidence of involuntary separation and hiring as dependent variables are presented in Panel B of Table 6. Columns (1) to (4) report estimates for managers and supervisors, while Columns (5) to (6) focus on clerical support employees. I find acquirers replace incumbent high-level managers but keep supervisors in the post-merger period. Specifically, the estimated coefficients in Columns (1) and (2) suggest managers experience a 6.3-percentage-point increase in involuntary separations that is followed by a 6.4-percentage-point increase in hiring. By contrast, mergers are associated with a decline in involuntary exit for supervisors and an increase in hiring. Finally, in Columns (5) and (6) I find no support that mergers lead to a leaner workforce through the decline in demand for employees in clerical support.

### 5.5 Mechanisms

In this section, I attempt to provide evidence on the mechanisms that explain the observed post-merger compositional changes by exploring three potential distinct and non-mutually exclusive channels. First, I hypothesize that the effects are expected to be larger for target firms in mergers with acquirers that have greater potential and ability to transfer technology and knowledge. Second, I directly explore investment in technology by focusing on management changes in positions that specifically engage in decisions regarding technology adoption and innovation. Finally, I consider the role of economies of scale and the relaxation of financial constraints in facilitating investment in technology.

#### 5.5.1 Knowledge and Technology Transfer

The previous findings suggest target firms experience technological transformation in the post-merger period by implementing changes in the labor composition towards occupational tasks that require non-routine, knowledge- and innovation-intensive skills. To the extent that the observed technological shifts are driven by acquirers transferring technologies and organizational practices to realize efficiency gains, the post-merger effects are expected to be larger in mergers with acquirers that have greater potential and ability to transfer technology

[26] Managers include the two-digit occupational codes 12.

[27] Clerical support employees are identified using the one-digit occupational code 4.

and knowledge. To explore this mechanism, I classify merger transactions using information on the pre-merger human capital characteristics of acquirers.

First, I capture the acquirers' potential to foster technological modernization and innovation practices by estimating the pre-merger distance in the shares of high-skilled, non-routine and innovation-intensive employees between acquirers and target firms. The larger the difference in the input-based measures of technological adoption and innovation intensity between the acquirer and target firm, the greater the potential for acquirers to realize efficiency gains by reorganizing target firms' labor force in a direction that is consistent with skill upgrade and technology adoption. As a result, I divide mergers into terciles based on the pre-merger distance in these human capital characteristics between acquirers and the target firms.

Second, acquirers on average have higher shares of high-skilled employees and are less routine-intensive relative to target firms prior to the merger. Neoclassical theories argue that mergers emerge as a vehicle of technological change (Jovanovic and Rousseau, 2008) where technologically advanced firms become acquirers and firms that lag in technology adoption become targets of merger activity. Therefore, I hypothesize that acquirers with higher levels of skill and innovation intensity are able to transfer organizational know-how and impose technological change. To capture an acquirer's comparative advantage and ability to impose technological modernization and skill upgrade, I leverage information on pre-merger human capital characteristics. Acquirers endowed with a skilled, less routine and innovation-intensive labor force have the skills, knowledge and resources to restructure the target firm's labor force in a direction that increases technology adoption. This feature may be particular salient in a developing setting such as Brazil, where a large part of the merger activity originates from firms in developed countries that possess superior knowledge-based assets and possess competitive advantages transferable to the market of the host country (e.g., Hymer, 1976). To test this prediction, I divide mergers into terciles based on acquirers' pre-merger high-skilled, non-routine and innovation-intensive share.

Table 7 presents the results from estimating Equation (5) for the subsample of merger transactions where the identity of the acquirer is available in RAIS.[28] Panel A reports the coefficient estimates for the terciles that capture pre-merger differences in human capital characteristics between acquirers and target firms, whereas Panel B reports estimates based on acquirers' pre-merger input-based measures of technology adoption. The estimates in Panel A suggest compositional shifts in target firms' human capital consistent with skill upgrade, increase in innovation intensity and adoption of labor-saving technologies occur only within mergers pairs wherein acquirers have a greater potential for knowledge and technology transfer. Similarly, the coefficient estimates in Panel B indicate that only the most skilled and technologically advanced acquirers foster skill- and routine-biased compositional changes to the labor force of target firms.

[28]Panel A of Table A7 in the Appendix present estimates from a triple difference specification.

Finally, Appendix Table A6 reports the results from estimating Equation (5) only for the subsample of mergers with a foreign acquirer. The results suggest cross-border mergers are associated with changes in the human capital of target firms indicative of skill upgrade and increases in non-routine and innovation intensity. These findings are consistent with stylized facts in the trade and international economics literature that highlight the benefits of foreign ownership (e.g., Guadalupe et al., 2012) and the link between increased international exposure and technological upgrade (Verhoogen, 2008; Bustos, 2011).

Overall, these findings highlight that increases in target firms' degree of technology adoption and innovation intensity are primarily driven by mergers with acquirers that have a greater potential and comparative advantage in transferring technology and imposing skill- and innovation-intensive organizational practices.

### 5.5.2 Management Changes

Previous findings provide evidence that mergers are followed by replacement of target firms' high-level management. In this section, I provide evidence that the merger effects are mainly concentrated on mergers wherein acquirers hire managers in positions that specifically engage in decisions regarding technology adoption and innovation. In addition, I hypothesize that the effects are expected to be larger for mergers in which acquirers replace target firms' managers with insider managers in an effort to facilitate knowledge transfer and instill better organizational practices (Bloom et al., 2013).

To test these hypotheses, I first consider the decision of acquirers to hire a Chief Executive Officer (CEO), a Chief Technology Officer (CTO) or a Chief Research Officer (CRO) for target firms in the post-merger period.[29] I identify employees in the relevant managerial positions by using information on the occupational codes assigned to employees in RAIS. Second, I investigate changes in the target firm's human capital composition when acquirers transfer an insider manager to the target firm. The results are reported in Table 8.

In Columns (3) to (6) of Panel A, I find a statistically significant decline in the share of routine employees and an increase in innovation intensity only for the set of target firms that hire a CEO, CTO or CRO in the post-merger period. However, I find no difference in the effect of mergers of skill intensity between the two groups. In Columns (1) to (6) of Panel B, I find the positive relationship between mergers and input-based measures of technological change to be larger in mergers where acquirers transfer an insider manager to target firms. However, the coefficient estimates of the triple difference are only statistically significant for the share of high-skilled employees, as reported in Table A7 in the Appendix. Overall, these

[29]The results are similar if I instead focus only on CTOs and CROs. In unreported results, I find no effects if I separately consider Chief Financial Officers, Chief Marketing Officers or Chief Human Resources Officers. This evidence provides further support of post-merger technological change, given that the effects are concentrated only on managerial positions relevant for technology adoption and innovation.

results provide some evidence that changes in management are an important channel that facilitates the adoption of technology and innovation practices in target firms.

### 5.5.3 Fixed Costs of Technological Upgrade and Financial Constraints

In this section, I consider the role of economies of scale and the relaxation of financial constraints in facilitating investment in technology. Cost synergies play an important role in value creation in mergers. To the extent that mergers are followed by occupational overlap that enables target firms to economize on labor expenses by decreasing the relative price of technological upgrade and investment in labor-saving technologies, I expect employees in overlapping occupations that perform routine tasks or tasks substitutable by technology to experience an increase in involuntary separations in the post-merger period. To test this hypothesis, I examine the impact of occupational overlap on the incidence of involuntary separations for employees in knowledge-intensive and routine occupations. The results from estimating Equation (7) are presented in Panel A of Table 9.

Columns (1) and (2) examine the relation between occupational overlap and the knowledge intensity of occupations, whereas Columns (3) and (4) focus on the routine task intensity of occupations. I find post-merger occupational overlap is associated with an increase in the likelihood of involuntary separations only for employees that perform tasks substitutable by technology. The magnitudes of the coefficient estimates suggest employees in occupations that are less knowledge-intensive experience a 2.3-percentage-point increase in the likelihood of involuntary separations that corresponds to an economically significant increase of 15% relative to the sample mean. Similarly, occupational overlap increases the the probability of involuntary separation by 2.7 percentage points for employees in routine occupations. Overall, I interpret these findings as evidence that occupational overlap in mergers allow target firms to exploit economies of scale and invest in technologies that disproportionately affects employees that perform tasks substitutable by technology.

Finally, I examine whether mergers allow target firms to invest in technology by mitigating financial constraints. Erel et al. (2015) present evidence that mergers alleviate financial constraints in target firms leading to an increase in investment. To the extent that investment in capital is followed by technology adoption that is complementary to high-skilled labor, an increase in investment would predict an increase in skill and non-routine intensity. To test this hypothesis, I use the target firm's size as a proxy for financial constraints (Hadlock and Pierce, 2010) and classify target firms into terciles based on the number of employees present at the time of the merger.[30] The estimates are reported in Panel B of Table 9.

Columns (1) and (2) report the coefficient estimates for the share of high-skilled employees, while Columns (3) and (4) present the results for the share of routine employees. The

[30]The results are similar if I, instead, use the size of the target firm at the year prior to the merger event.

magnitudes of the coefficient estimates indicate that the increase in the share of high-skilled employees is large and statistically significant only for smaller targets with an estimated post-merger increase of 3.8 percentage points. Similarly, there is statistically significant 2.6-percentage-point decline in the share of routine employees only for the subsample of smaller targets. These results provide suggestive evidence that mergers enable target firms to invest in technology by mitigating financial constraints.

### 5.6 Convergence Between Acquirers and Targets and Productivity Changes

In this section, I provide evidence of post-merger convergence between the human capital composition of acquirers and target firms. For this purpose, I create variables that measure the absolute difference between the acquirer and the target firm for the set of human capital characteristics that capture skill, routine and innovation intensity. Then, I estimate the following firm-level empirical specification:

$$\Delta Y_{it} = \alpha_i + \alpha_t + \gamma Post_p + \varepsilon_{jt} \tag{9}$$

The unit of analysis is an acquirer-target pair and a negative coefficient $\gamma$ implies that mergers are followed by convergence in the characteristic $Y_{it}$. The coefficient estimates are reported in Panel A of Table 10. Columns (1) to (3) report estimates for characteristics that capture differences in skill composition and demonstrate that acquirers and target firms converge in terms of skill intensity. For example, the magnitudes of the coefficient estimates in Column (3) suggest the difference in the share of high-skilled employees declines in the post-merger period by 1.8 percentage points or 12% relative to the sample mean. Columns (4) to (5) present estimates for differences in routine composition. I find the share of routine employees converges by 2.4 percentage points or 16% relative to the sample mean. Finally, as demonstrated in Column (6), mergers are followed by a decline in the innovation intensity between acquirers and targets by 0.6 percentage points. These findings are consistent with acquirers actively restructuring target firms' labor inputs in the post-merger period and generating efficiency gains by imposing common practices.

Finally, I attempt to provide suggestive evidence that mergers are associated with increases in productivity and innovation efficiency in the post-merger period. An important caveat with the RAIS dataset is that no information exists on firms' financial and operating performance. However, I investigate productivity changes using two measures that potentially capture operating and innovation efficiency. First, I use the firm fixed effects estimates from the AKM estimation as a proxy of productivity changes as described in Section 3.2. Specifically, I follow Card et al. (2013) and estimate values for the AKM firm fixed effect for the six-year period before and after the merger including the event year in both estimations. Second, I collect information on firm-level patenting activity from the Brazilian Patent Office. One concern is that patenting is relatively uncommon in Brazil with only 10% of the firms in my

sample having at least one patent during the period under study. However, the advantage of using patent data is that I capture the efficiency of the firms' innovation activities.

The estimates are presented in Panel B of Table 10. Column (1) focuses on the AKM firm fixed effect and provides suggestive evidence that target firms perform better in the post-merger period relative to the set of control firms. Column (2) examine the probability of generating a patent before and after the merger by using as dependent variable an indicator function that is equal to one if a firm has generated a patent in the pre- or post-merger period and zero otherwise. The magnitude of the coefficient estimate suggests a 4.9-percentage-point increase in the probability of patenting in the post-merger for target firms relative to the set of counterfactual firms. Column (3) provides evidence that the probability of a firm patenting for the first time in the post-merger period is 3.1 percentage points higher for target firms. Finally, Columns (4) and (6) employ different specifications to measure innovation output (OLS and count models) and provide estimates indicative of an increase in the number of patents for target firms in the post-merger period. These findings provide empirical support that the observed post-merger changes in labor composition are followed by an increase in technological efficiency and productivity.

### 5.7 Alternative Merger Motivations

Overall, this paper provides evidence in line with neoclassical merger theories that highlight the role of synergy gains and efficiency improvements in the production process as the primary merger motivation. Although analyzing what precisely drives mergers is beyond the scope of the article, there is a significant part of the literature that instead emphasizes the role of non-efficiency considerations such as empire-building, managerial hubris, market power as drivers of merger activity (e.g., Jensen, 1986; Roll, 1986).

To allow for the possibility of empire-building, I classify mergers based on whether the acquirer engages in multiple acquisitions. From an agency theory perspective, mergers from serial acquirers are likely driven by managers that engage in empire building. For this purpose, I extend Equation (5) by estimating the following triple-difference specification:

$$\begin{aligned} Y_{itm} = \alpha_i + \alpha_t + \gamma Post_p + \delta Post_p \times I_i^{Treated} + \theta Post_p \times I_i^{SerialAcquirer} + \\ + \eta Post_p \times I_i^{Treated} \times I_i^{C} + \varepsilon_{itm} \end{aligned} \tag{10}$$

The estimates are reported in Appendix Table A8. I find no differences in the labor composition between mergers that involve serial acquirers and mergers that do not, implying that mergers by serial acquirers are not associated with destructive restructuring of human capital. While these findings suggest that restructuring of human capital is not primarily driven by empirical-building considerations, they do not preclude the existence of other forms of agency problems or that there may be mergers driven by agency considerations. Nor do they

rule out inefficiencies associated with overpayment or wealth transfers from acquirer to target shareholders. However, the paper's baseline results demonstrate that the reorganization of the labor force reflects skill-intensive and routine-biased shifts in labor demand, which are associated with efficient consolidation and cost-reduction practices.

# 6 Conclusion

In this paper, I examine the relation between firms' human capital composition and mergers using detailed employer-employee administrative data linked with hand-collected information on merger activity in Brazil from 2004 to 2012. To identify the mechanisms through which mergers generate efficiency gains, I develop input-based measures that capture different dimensions of organizational change by relying on textual analysis of the description of occupational tasks performed by employees. Using these measures, I am able to provide an in-depth analysis of the impact of mergers on the organizational boundaries of firms and draw inferences regarding the underlying merger motivations and sources of value creation.

Consistent with positive selection in terms of human capital, mergers occur between firms with a greater share of high-skilled employees and innovation intensity are more likely to be involved in mergers. However, acquirers are less routine-intensive compared to peer firms, whereas target firms exhibit higher levels of routine intensity. In line with the importance of synergy gains in mergers, occupational overlap is an important determinant of merger pair formation. Investigating ex post treatment effects of mergers, I document that mergers are associated with extensive shifts in target firms' composition of human capital that reflect efficiency-seeking restructuring through technology adoption, investment in innovation and cost synergies. There are several non-mutually exclusive mechanisms that explain the observed post-merger shifts in labor demand. I provide strong evidence that mergers act as a vehicle of knowledge transfers from acquirers that have the potential and ability to do so. In addition, economies of scale that affect the relative price of investment in technology and adoption of labor-saving technology is an important mechanism through which mergers alter the human capital composition.

My findings have broader implications about how acquirers redraw target firms' boundaries after mergers. First, the observed positive selection suggests that there are complementarities between technology adoption and the initial characteristics of the target firm. Second, given the extent of post-merger changes in the composition of human capital, mergers should be viewed not only as a mechanism that generates efficiency gains from exploiting occupational redundancies but also as a vehicle of extensive organizational changes that reset the boundaries of the firms in a manner that is indicative of technological change and efficiency-seeking consolidation.

## References

Abowd, J. M., J. Haltiwanger, R. Jarmin, J. Lane, P. Lengermann, K. McCue, K. McKinney, and K. Sandusky (2005). The Relation among Human Capital, Productivity, and Market Value: Building up from Micro Evidence. In *Measuring Capital in the New Economy*, pp. 153–204. University of Chicago Press.

Abowd, J. M., F. Kramarz, and D. N. Margolis (1999). High Wage Workers and High Wage Firms. *Econometrica 67*(2), 251–333.

Agrawal, A. and P. Tambe (2016). Private Equity and Workers' Career Paths: the Role of Technological Change. *The Review of Financial Studies 29*(9), 2455–2489.

Agrawal, A. K. and D. A. Matsa (2013). Labor Unemployment Risk and Corporate Financing Decisions. *Journal of Financial Economics 108*(2), 449–470.

Almeida, H., M. Campello, and D. Hackbarth (2011). Liquidity Mergers. *Journal of Financial Economics 102*(3), 526–558.

Alvarez, J., F. Benguria, N. Engbom, and C. Moser (2018). Firms and the Decline in Earnings Inequality in Brazil. *American Economic Journal: Macroeconomics 10*(1), 149–189.

Andrade, G., M. L. Mitchell, and E. Stafford (2001). New Evidence and Perspectives on Mergers. *Journal of Economic Perspectives* (15), 103–120.

Andrews, M. J., L. Gill, T. Schank, and R. Upward (2012). High Wage Workers Match with High Wage Firms: Clear Evidence of the Effects of Limited Mobility Bias. *Economics Letters 117*(3), 824–827.

Antoni, M., E. Maug, and S. Obernberger (2019). Private Equity and Human Capital Risk. *Journal of Financial Economics 133*(3), 634–657.

Arnold, D. (2020). Mergers and Acquisitions, Local Labot Market Concentration, and Worker Outcomes. *Available at SSRN 3476369*.

Autor, D. H., F. Levy, and R. J. Murnane (2003, 11). The Skill Content of Recent Technological Change: An Empirical Exploration*. *The Quarterly Journal of Economics 118*(4), 1279–1333.

Autor, H. and D. Dorn (2013). The Growth of Low-Skill Service Jobs and the Polarization of the US Labor Market. *The American Economic Review 103*(5), 1553–1597.

Baghai, R., R. Silva, V. Thell, and V. Vig (2016). Talent in Distressed Firms: Investigating the Labor Costs of Financial Distress. *Working Paper*.

Bartel, A., C. Ichniowski, and K. Shaw (2007). How Does Information Technology Affect Productivity? Plant-Level Comparisons of Product Innovation, Process Improvement, and Worker Skills. *The Quarterly Journal of Economics 122*(4), 1721–1758.

Bena, J. and K. Li (2014). Corporate innovations and mergers and acquisitions. *The Journal of Finance 69*(5), 1923–1960.

Bertrand, M. and S. Mullainathan (2003). Enjoying the Quiet Life? Corporate Governance and Managerial Preferences. *Journal of Political Economy 111*(5), 1043–1075.

Bloom, N., B. Eifert, A. Mahajan, D. McKenzie, and J. Roberts (2013). Does Management Matter? Evidence from India. *The Quarterly Journal of Economics 128*(1), 1–51.

Botero, J. C., S. Djankov, R. L. Porta, F. Lopez-de Silanes, and A. Shleifer (2004). The Regulation of Labor. *The Quarterly Journal of Economics 119*(4), 1339–1382.

Bresnahan, T. F., E. Brynjolfsson, and L. M. Hitt (2002). Information Technology, Workplace Organization, and the Demand for Skilled Labor: Firm-Level Evidence. *The Quarterly Journal of Economics 117*(1), 339–376.

Brown, C. and J. L. Medoff (1988). The Impact of Firm Acquisitions on Labor. In *Corporate Takeovers: Causes and Consequences*, pp. 9–32. University of Chicago Press.

Bustos, P. (2011). Trade Liberalization, Exports, and Technology Upgrading: Evidence on the Impact of MERCOSUR on Argentinian Firms. *The American Economic Review 101*(1), 304–340.

Bustos, P., J. M. C. Vincenzi, J. Monras, and J. Ponticelli (2019). Structural Transformation, Industrial Specialization, and Endogenous Growth. *Working Paper, National Bureau of Economic Research*.

Card, D., A. R. Cardoso, J. Heining, and P. Kline (2018). Firms and Labor Market Inequality: Evidence and Some Theory. *Journal of Labor Economics 36*(S1), S13–S70.

Card, D., J. Heining, and P. Kline (2013). Workplace Heterogeneity and the Rise of West German Wage Inequality. *The Quarterly Journal of Economics 128*(3), 967–1015.

Christensen, B. J., R. Lentz, D. T. Mortensen, G. R. Neumann, and A. Werwatz (2005). On-the-job Search and the Wage Distribution. *Journal of Labor Economics 23*(1), 31–58.

Conyon, M. J., S. Girma, S. Thompson, and P. W. Wright (2002). The Impact of Mergers and Acquisitions on Company Employment in the United Kingdom. *European Economic Review 46*(1), 31–49.

Davis, S. J., J. Haltiwanger, K. Handley, R. Jarmin, J. Lerner, and J. Miranda (2014). Private Equity, Jobs, and Productivity. *The American Economic Review 104*(12), 3956–3990.

Dessaint, O., A. Golubov, and P. Volpin (2017). Employment Protection and Takeovers. *Journal of Financial Economics 125*(2), 369–388.

Devos, E., P.-R. Kadapakkam, and S. Krishnamurthy (2009). How Do Mergers Create Value? A Comparison of Taxes, Market Power, and Efficiency Improvements as Explanations for Synergies. *The Review of Financial Studies 22*(3), 1179–1211.

Dix-Carneiro, R. (2014). Trade Liberalization and Labor Market Dynamics. *Econometrica 82*(3), 825–885.

Erel, I., Y. Jang, and M. S. Weisbach (2015). Do Acquisitions Relieve Target Firms' Financial Constraints? *The Journal of Finance 70*(1), 289–328.

Gort, M. (1969). An Economic Disturbance Theory of Mergers. *The Quarterly Journal of Economics*, 624–642.

Graham, J. R., H. Kim, S. Li, and J. Qiu (2019). Employee Costs of Corporate Bankruptcy. *Working Paper, National Bureau of Economic Research*.

Guadalupe, M., O. Kuzmina, and C. Thomas (2012, December). Innovation and foreign ownership. *American Economic Review 102*(7), 3594–3627.

Hadlock, C. J. and J. R. Pierce (2010). New Evidence on Measuring Financial Constraints: Moving Beyond the KZ Index. *The Review of Financial Studies 23*(5), 1909–1940.

Hoberg, G. and G. Phillips (2010). Product Market Synergies and Competition in Mergers and Acquisitions: A Text-based Analysis. *The Review of Financial Studies 23*(10), 3773–3811.

Holmstrom, B. and J. Roberts (1998, December). The boundaries of the firm revisited. *Journal of Economic Perspectives 12*(4), 73–94.

Hymer, S. H. (1976). *International Operations of National Firms*. MIT press.

Jensen, M. C. (1986). Agency Costs of Free Cash Flow, Corporate Finance, and Takeovers. *The American Economic Review 76*(2), 323–329.

Jensen, M. C. and R. S. Ruback (1983). The Market for Corporate Control: The Scientific Evidence. *Journal of Financial Economics 11*(1-4), 5–50.

Jovanovic, B. and P. L. Rousseau (2002). The Q-Theory of Mergers. *American Economic Review 92*(2), 198–204.

Jovanovic, B. and P. L. Rousseau (2008). Mergers as Reallocation. *The Review of Economics and Statistics 90*(4), 765–776.

Kaplan, S. N. and M. S. Weisbach (1992). The Success of Acquisitions: Evidence from Divestitures. *The Journal of Finance 47*(1), 107–138.

Katz, L. F. and D. H. Autor (1999). *Changes in the Wage Structure and Earnings Inequality*, pp. 1463–1555.

Lee, K. H., D. C. Mauer, and E. Q. Xu (2018). Human Capital Relatedness and Mergers and Acquisitions. *Journal of Financial Economics 129*(1), 111–135.

Li, X. (2013). Productivity, Restructuring, and the Gains from Takeovers. *Journal of Financial Economics 109*(1), 250–271.

Lichtenberg, F. R. and D. Siegel (1990). The Effect of Ownership Changes on the Employment and Wages of Central Office and Other Personnel. *The Journal of Law and Economics 33*(2), 383–408.

Lichtenberg, F. R., D. Siegel, D. Jorgenson, and E. Mansfield (1987). Productivity and Changes in Ownership of Manufacturing Plants. *Brookings Papers on Economic Activity 1987*(3), 643–683.

Lopes de Melo, R. (2018). Firm Wage Differentials and Labor Market Sorting: Reconciling Theory and Evidence. *Journal of Political Economy 126*(1), 313–346.

Ma, W., P. P. Ouimet, and E. Simintzi (2019). Mergers and Acquisitions, Technological Change and Inequality. *Working Paper*.

Maksimovic, V. and G. Phillips (2001). The Marker for Corporate Assets: Who Engages in Mergers and Asset Sales and Are There Efficiency Gains? *The Journal of Finance 56*(6), 2019–2065.

Maksimovic, V., G. Phillips, and N. R. Prabhala (2011). Post-Merger Restructuring and the Boundaries of the Firm. *Journal of Financial Economics 102*(2), 317–343.

Manne, H. G. (1965). Mergers and the Market for Corporate Control. *Journal of Political Economy 73*(2), 110–120.

Martin, K. J. and J. J. McConnell (1991). Corporate Performance, Corporate Takeovers, and Management Turnover. *The Journal of Finance 46*(2), 671–687.

McGuckin, R. H. and S. V. Nguyen (2001). The Impact of Ownership Changes: A View from Labor Markets. *International Journal of Industrial Organization 19*(5), 739–762.

Mitchell, M. L. and J. H. Mulherin (1996). The Impact of Industry Shocks on Takeover and Restructuring Activity. *Journal of Financial Economics 41*(2), 193–229.

Muendler, M.-A., J. Poole, G. Ramey, and T. Wajnberg (2004). Job Concordances for Brazil: Mapping the Classificaçao Brasileira de Ocupaçoes (CBO) to the International Standard Classification of Occupations (ISCO-88). Technical report, University of California, San Diego.

Olsson, M. and J. Tåg (2017). Private Equity, Layoffs, and Job Polarization. *Journal of Labor Economics 35*(3), 697–754.

Ouimet, P. and R. Zarutskie (2016). Aquiring Labor. *Working Paper*.

Pagano, M. and P. F. Volpin (2005). Managers, workers, and corporate control. *The Journal of Finance 60*(2), 841–868.

Prager, E. and M. Schmitt (2021, February). Employer consolidation and wages: Evidence from hospitals. *American Economic Review 111*(2), 397–427.

Rhodes-Kropf, M. and D. T. Robinson (2008). The Market for Mergers and the Boundaries of the Firm. *The Journal of Finance 63*(3), 1169–1211.

Roll, R. (1986). The Hubris Hypothesis of Corporate Takeovers. *Journal of Business*, 197–216.

Serafinelli, M. (2019). Good Firms, Worker Flows and Local Productivity. *Journal of Labor Economics 37*(3), 747–792.

Sheen, A. (2014). The Real Product Market Impact of Mergers. *The Journal of Finance 69*(6), 2651–2688.

Shleifer, A. and L. H. Summers (1988). Breach of Trust in Hostile Takeovers. In *Corporate Takeovers: Causes and Consequences*, pp. 33–68. University of Chicago Press.

Tate, G. and L. Yang (2015). The Bright Side of Corporate Diversification: Evidence from Internal Labor Markets. *The Review of Financial Studies 28*(8), 2203–2249.

Tate, G. A. and L. Yang (2016). The Human Factor in Acquisitions: Cross-Industry Labor Mobility and Corporate Diversification. *Working Paper*.

Verhoogen, E. A. (2008). Trade, Quality Upgrading, and Wage Inequality in the Mexican Manufacturing Sector. *The Quarterly Journal of Economics 123*(2), 489–530.

Villalonga, B., J. A. Davis, and R. R. de Pinho (2012). *Itaú Unibanco (A): The Merger Process*. Harvard Business School.

Zingales, L. (2000). In Search of New Foundations. *The Journal of Finance 55*(4), 1623–1653.

# Figures

**Figure 1:** Matched Sample of Publicly Announced and Completed M&A Transactions in Brazil. Source: Thomson SDC and RAIS

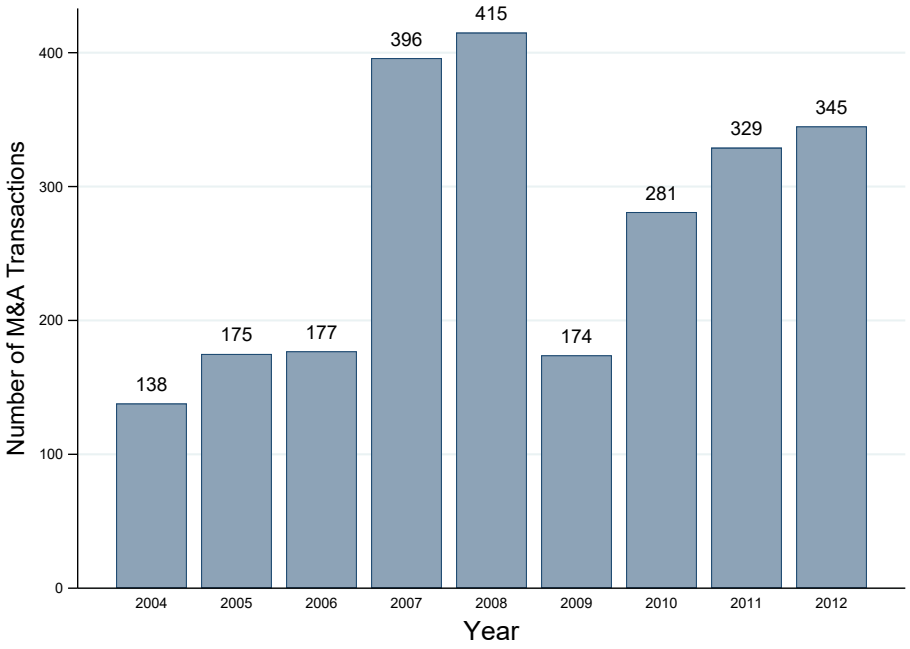



**Figure 2:** Size of Target Firms Vs. Population

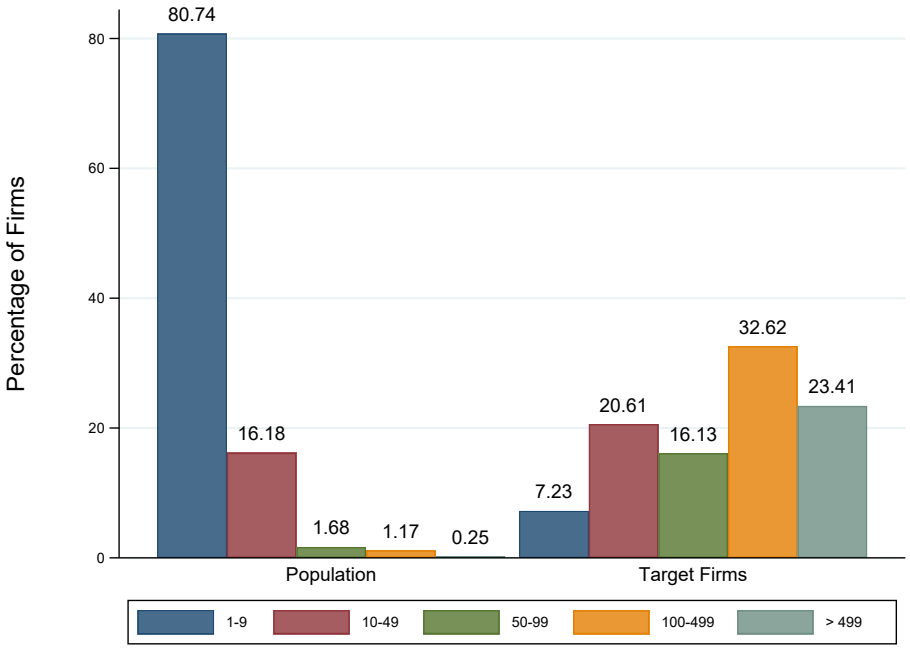
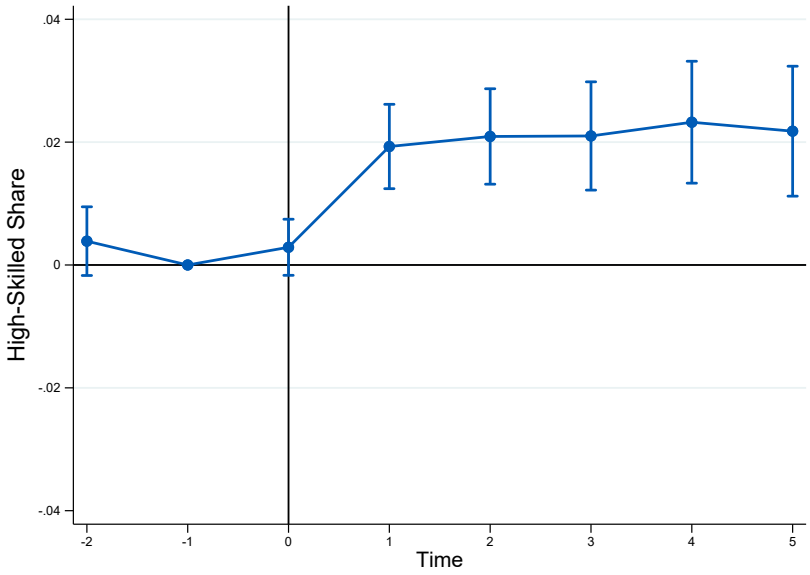
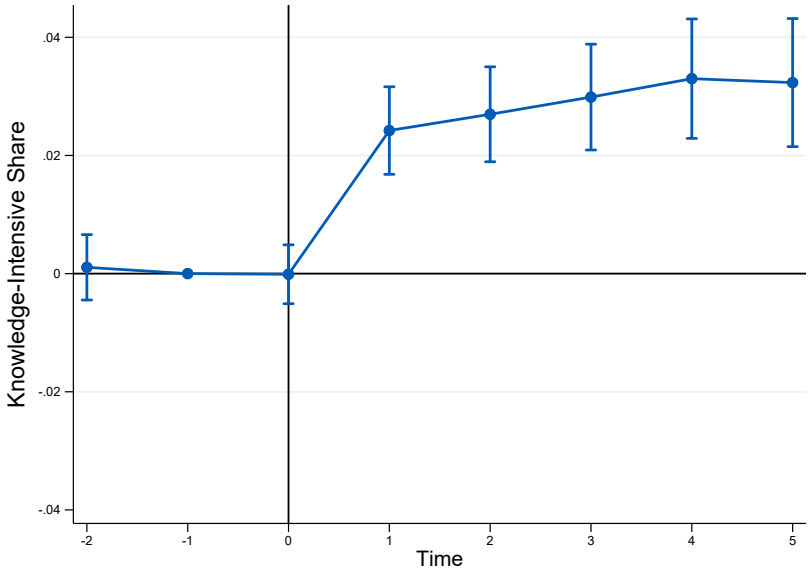


**Figure 3:** Dynamic Effects of Mergers on Target's Share of High-Skilled Employees



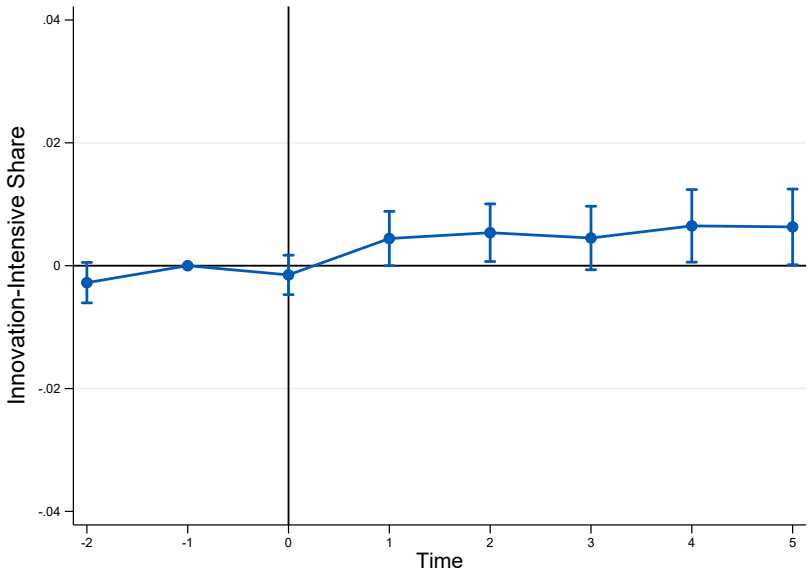

**Notes:** The figure reports estimates from Equation (6) using the share of high-skilled employees at target firms as the dependent variable.

**Figure 4:** Dynamic Effects of Mergers on Target's Share of Employees in Knowledge-Intensive Occupations



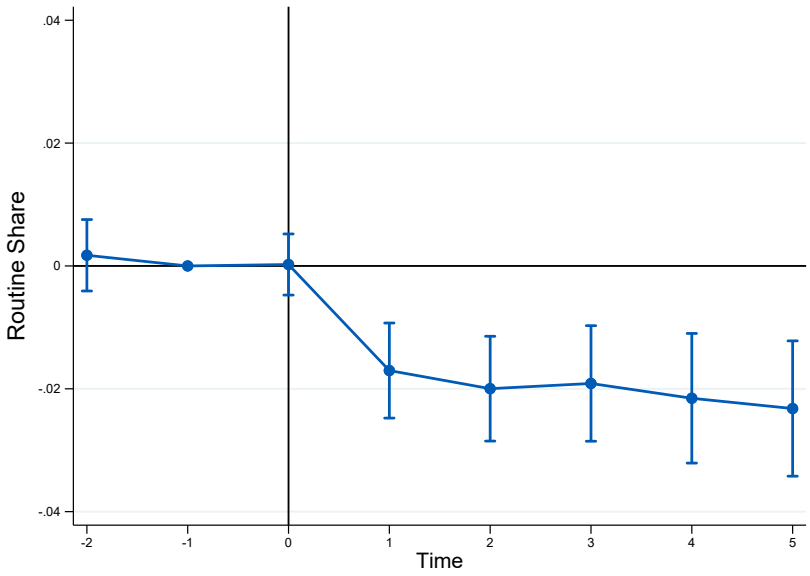

**Notes:** The figure reports estimates from Equation (6) using the share of employees in knowledge-intensive occupations at target firms as the dependent variable.

**Figure 5:** Dynamic Effects of Mergers on Target's Share of Employees in Innovation-Intensive Occupations




**Notes:** The figure reports estimates from Equation (6) using the share of employees in innovation-intensive occupations at target firms as the dependent variable.

**Figure 6:** Dynamic Effects of Mergers on Target's Share of Employees in Routine Occupations




**Notes:** The figure reports estimates from Equation (6) using the share of employees in routine occupations at target firms as the dependent variable.

# Tables

**Table 1: Merger Characteristics**

| | (1) | (2) | (3) |
|---|---|---|---|
| **Panel A: Characteristics of M&A Deals** | | | |
| **Variables** | **Number of Deals** | **Mean** | **SD** |
| Public Acquirer | 2,104 | 0.31 | 0.46 |
| Public Target | 2,104 | 0.03 | 0.16 |
| Focused | 2,104 | 0.73 | 0.45 |
| Foreign Acquirer | 2,104 | 0.42 | 0.49 |
| **Panel B: M&A Sectors** | | | |
| **Sector** | **Number of Deals** | **Percentage Share** | **% Foreign Acquisitions** |
| Agriculture/Mining | 95 | 0.04 | 0.41 |
| Low-Tech Manufacturing | 430 | 0.18 | 0.50 |
| High-Tech Manufacturing | 347 | 0.14 | 0.61 |
| Construction | 56 | 0.02 | 0.39 |
| Trade | 314 | 0.13 | 0.45 |
| Transportation/Utilities | 247 | 0.10 | 0.25 |
| Services | 941 | 0.39 | 0.36 |
| **Panel C: Disposal of Target Establishments and Employee Transfers** | | | |
| **Number of Establishments** | **Disposal Rate (Establishments)** | **% of Total Employees** | **Transfer Rate (Employees)** |
| 1 - 5 | 55.2% | 52.3% | 43.6% |
| 6 - 10 | 61.3% | 52.5% | 40.9% |
| 11 - 50 | 67.3% | 57.5% | 46.2% |
| $> 50$ | 57.3% | 48.8% | 66.2% |
| Total | 56.5% | 52.6% | 56.4% |

**Notes:** The table reports descriptive statistics. Panel A reports descriptive statistics for characteristics of merger deals. Panel B reports descriptive statistics for the sectors in which target firms operate. Panel C reports descriptive statistics on the disposal rates of target firms' establishments and within-firm employee transfers.
Significance Levels: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

**Table 2: Summary Statistics**

| **Panel A: Target Firms** | | | | | | |
|---|---|---|---|---|---|---|
| | **Target Firms** | | | **Sector- and Size-Matched Firms** | | |
| **Variables** | **Mean** | **SD** | **Median** | **Mean** | **SD** | **Median** |
| Employment | 634 | 2,558 | 126 | 548** | 1,545 | 131 |
| Monthly Average Wage (R$) | 1,328 | 1,174 | 1,000 | 1,217*** | 1,092 | 883*** |
| Log Employment | 4.89 | 1.72 | 4.84 | 4.89 | 1.72 | 4.88 |
| Log Monthly Average Wage | 6.75 | 0.58 | 6.68 | 6.67*** | 0.60 | 6.58*** |
| Years of Education | 12.63 | 1.97 | 12.64 | 12.00*** | 2.15 | 12.00*** |
| High-Skilled Share | 0.32 | 0.28 | 0.22 | 0.25*** | 0.27 | 0.14*** |
| RTI | 1.56 | 1.01 | 1.58 | 1.49*** | 1.06 | 1.51** |
| Innovation-Intensive Share | 0.10 | 0.17 | 0.04 | 0.08*** | 0.16 | 0.02*** |
| Blue-Collar Share | 0.28 | 0.31 | 0.10 | 0.32*** | 0.33 | 0.20*** |
| **Panel B: Acquirers** | | | | | | |
| | **Acquirers** | | | **Sector- and Size-Matched Firms** | | |
| **Variables** | **Mean** | **SD** | **Median** | **Mean** | **SD** | **Median** |
| Employment | 3,367 | 8,456 | 668 | 2,418*** | 6,461 | 610 |
| Monthly Average Wage (R$) | 1,820 | 1,864 | 1,353 | 1,490*** | 1,553 | 1,034*** |
| Log Employment | 6.38 | 2.09 | 6.51 | 6.22** | 2.06 | 6.42 |
| Log Monthly Average Wage | 6.97 | 0.65 | 6.88 | 6.78*** | 0.68 | 6.67*** |
| Years of Education | 13.04 | 1.90 | 13.08 | 12.15*** | 2.43 | 12.36*** |
| High-Skilled Share | 0.39 | 0.28 | 0.31 | 0.30*** | 0.28 | 0.19*** |
| RTI | 1.50 | 0.93 | 1.48 | 1.50 | 1.08 | 1.48 |
| Innovation-Intensive Share | 0.10 | 0.16 | 0.05 | 0.08*** | 0.15 | 0.03*** |
| Blue-Collar Share | 0.26 | 0.30 | 0.10 | 0.32*** | 0.33 | 0.17*** |
| **Panel C: Acquirer-Target Firm Pairs** | | | | | | |
| | **Acquirer-Target Firm Pairs** | | | **Sector- and Size-Matched Firm Pairs** | | |
| **Variables** | **Mean** | **SD** | **Median** | **Mean** | **SD** | **Median** |
| Occupational Proximity | 0.35 | 0.30 | 0.23 | 0.25*** | 0.27 | 0.14*** |
| Occupational Overlap | 0.18 | 0.11 | 0.17 | 0.13*** | 0.08 | 0.12*** |
| Occupational Overlap (Target) | 0.52 | 0.23 | 0.53 | 0.38*** | 0.20 | 0.37*** |
| Occupational Overlap (Acquirer) | 0.28 | 0.19 | 0.24 | 0.21*** | 0.15 | 0.18*** |
| ΔEducation | 1.01 | 1.09 | 0.72 | 1.54*** | 1.52 | 1.08*** |
| ΔHigh-Skilled Share | 0.15 | 0.16 | 0.10 | 0.20*** | 0.20 | 0.13*** |
| ΔRTI | 0.72 | 0.72 | 0.48 | 0.92*** | 0.89 | 0.65*** |

**Notes:** The table reports summary statistics on human capital characteristics for acquirers and target firms as well as their sector- and size-matched control firms. Panel A presents descriptive characteristics for target firms, whereas Panel B reports descriptive statistics for acquirers. Panel C reports descriptive statistics on measures of occupational overlap and distance in human capital characteristics for acquirer-target firm pairs. The control sample in Panel C includes control merger pairs formed by pairing the acquirer and the target firm with up to five counterfactual firms based on a propensity score matching estimator using sector and size.
Significance Levels: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

**Table 3: Which Firms Merge?**

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
|---|---|---|---|---|---|---|---|---|
| **Variables** | **Target {0,1}** | | | **Acquirer {0,1}** | | | **Target-Acquirer Pair {0,1}** | |
| | **Total Sample** | **Sector, Size Sample** | | **Total Sample** | **Sector, Size Sample** | | **Sector, Size Sample** | |
| Years of Education | 0.0001*** | 0.0503*** | | 0.0001*** | 0.0646*** | | | |
| | (0.0000) | (0.0033) | | (0.0000) | (0.0039) | | | |
| RTI | -0.0000 | 0.0109** | | -0.0001*** | -0.0180*** | | | |
| | (0.0000) | (0.0048) | | (0.0000) | (0.0053) | | | |
| Innovation-Intensive Share | 0.0009*** | 0.0800** | | 0.0005*** | 0.0383 | | | |
| | (0.0001) | (0.0377) | | (0.0001) | (0.0503) | | | |
| Blue-Collar Share | -0.0000 | -0.0052 | | -0.0000 | 0.0381 | | | |
| | (0.0000) | (0.0209) | | (0.0000) | (0.0277) | | | |
| Average Occupational Proximity (Population) | | | 0.2683*** | | | 0.3876*** | | |
| | | | (0.0818) | | | (0.0974) | | |
| Average Occupational Proximity (Size-Sector) | | | -0.1170*** | | | -0.2283*** | | |
| | | | (0.0335) | | | (0.0375) | | |
| Log Employment | 0.0006*** | 0.0413*** | 0.0402*** | 0.0008*** | 0.0816*** | 0.0882*** | | |
| | (0.0000) | (0.0094) | (0.0091) | (0.0000) | (0.0109) | (0.0107) | | |
| Log Wage | 0.0008*** | 0.0656*** | 0.1591*** | 0.0009*** | 0.0936*** | 0.2195*** | | |
| | (0.0000) | (0.0149) | (0.0139) | (0.0000) | (0.0155) | (0.0126) | | |
| Occupational Proximity (Pair) | | | | | | | 0.2295*** | |
| | | | | | | | (0.0342) | |
| Occupational Overlap (Target) | | | | | | | | 0.5736*** |
| | | | | | | | | (0.0579) |
| Occupational Overlap (Acquirer) | | | | | | | | 0.4015*** |
| | | | | | | | | (0.0380) |
| ΔEducation | | | | | | | -0.0458*** | -0.0304*** |
| | | | | | | | (0.0088) | (0.0060) |
| ΔRTI | | | | | | | -0.0153** | -0.0166*** |
| | | | | | | | (0.0060) | (0.0040) |
| Sector × Year FE | Yes | No | No | Yes | No | No | No | No |
| Transaction FE | No | Yes | Yes | No | Yes | Yes | Yes | Yes |
| Observations | 5,885,240 | 12,307 | 12,256 | 5,889,260 | 8,384 | 8,350 | 16,748 | 16,748 |
| $R^2$ | 0.0004 | 0.0502 | 0.0220 | 0.0061 | 0.0987 | 0.0676 | 0.1506 | 0.2249 |

**Notes:** The table reports estimates on the linear probability of participating in a merger from Equation (3) and of forming a merger pair from Equation (4). Columns (1) and (4) use as control firms the population of firms that are present in RAIS for at least four years and employ at least five employees, whereas Columns (2), (3), (5) and (6) restrict the analysis to the set of sector- and size-matched control firms. In Columns (1) to (3) the dependent variable is an indicator variable that is equal to one if a firm is involved in merger transaction as a target firm, and zero otherwise. In Columns (4) to (6) the dependent variable is an indicator variable that is equal to one if a firm is involved in merger transaction as an acquirer, and zero otherwise. In Columns (7) and (8) the dependent variable is an indicator variable that is equal to one if a merger transaction occurs between a firm pair, and zero otherwise.
Significance Levels: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

**Table 4: The Impact of M&As on Skill Composition**

| | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| **Panel A: Joiners Vs. Leavers** | | | | | | |
| **Variables** | **Years of Education** | | | **Person Fixed Effects** | | |
| | **Total Labor Force** | **Leavers (Involuntary)** | **Joiners** | **Total Labor Force** | **Leavers (Involuntary)** | **Joiners** |
| Post × $I_j^{Treated}$ | 0.139*** | 0.022 | 0.321*** | 0.008*** | 0.001 | 0.024*** |
| | (0.022) | (0.035) | (0.050) | (0.003) | (0.004) | (0.005) |
| $R^2$ | 0.47 | 0.50 | 0.50 | 0.32 | 0.29 | 0.33 |
| Observations | 29,817,643 | 4,519,614 | 8,915,811 | 25,939,702 | 3,836,543 | 6,811,643 |
| **Panel B: Demand for High-Skilled Labor** | | | | | | |
| **Variables** | **Years of Education** | | **Person Fixed Effects** | | **Knowledge-Intensive Occupations** | |
| | **Involuntary Separation {0,1}** | **Hired {0,1}** | **Involuntary Separation {0,1}** | **Hired {0,1}** | **Involuntary Separation {0,1}** | **Hired {0,1}** |
| Post × $I_j^{Treated}$ × $I_j^{High-Skilled}$ | -0.034*** | 0.066*** | -0.024*** | 0.047*** | -0.029*** | 0.054*** |
| | (0.010) | (0.012) | (0.008) | (0.010) | (0.011) | (0.013) |
| Post × $I_j^{Treated}$ | 0.048*** | -0.063*** | 0.046*** | -0.055*** | 0.045*** | -0.056*** |
| | (0.011) | (0.013) | (0.009) | (0.013) | (0.010) | (0.012) |
| Post × $I_j^{High-Skilled}$ | -0.001 | -0.012** | -0.001 | -0.008 | 0.004 | -0.012** |
| | (0.008) | (0.005) | (0.005) | (0.006) | (0.008) | (0.005) |
| $I_j^{Treated}$ × $I_j^{High-Skilled}$ | 0.008 | -0.001 | 0.004 | -0.009 | 0.007 | -0.006 |
| | (0.007) | (0.009) | (0.006) | (0.009) | (0.008) | (0.009) |
| $I_j^{High-Skilled}$ | -0.026*** | -0.042*** | -0.034*** | -0.027*** | -0.034*** | -0.041*** |
| | (0.006) | (0.005) | (0.005) | (0.007) | (0.006) | (0.006) |
| $R^2$ | 0.08 | 0.22 | 0.08 | 0.19 | 0.08 | 0.22 |
| Observations | 29,817,643 | 29,817,643 | 25,939,702 | 25,939,702 | 29,817,643 | 29,817,643 |
| Employee Controls | Yes | Yes | Yes | Yes | Yes | Yes |
| Firm FE | Yes | Yes | Yes | Yes | Yes | Yes |
| Year FE | Yes | Yes | Yes | Yes | Yes | Yes |
| Event Year FE | Yes | Yes | Yes | Yes | Yes | Yes |

**Notes:** Panel A reports estimates from Equation (8) for the sample of employees in target and control firms. In Columns (1) to (3) of Panel A the dependent variable is the educational attainment of an employee in an event year measured using years of education, while in Columns (4) to (6) of Panel A the dependent variable is the employee-specific person fixed effect as estimated from the AKM specification. Columns (2) and (4) of Panel A report estimates only for the years when employees involuntarily exit the firm, while Columns (3) and (6) of Panel A report estimates only for the years when employees join the firm. Panel B reports estimates from Equation (7) for the sample of employees in target and control firms. In Columns (1), (3) and (5) of Panel B the dependent variable is an indicator variable that is equal to one in the year when an involuntary separation occurs. In Columns (2), (4) and (6) of Panel B the dependent variable is an indicator variable that is equal to one in the year when an employee is hired. $I_j^{High-Skilled}$ is an indicator function equal to one (i) for employees that have some undergraduate education in Columns (1) and (2) of Panel B, (ii) for employees with AKM person effect in the top quartile in Columns (3) and (4) of Panel B, and (iii) for employees in knowledge-intensive occupations in Columns (5) and (6) of Panel B. *Post* is an indicator variable that equals one for the five-year period after the merger transaction, and zero for the two-year period prior to the merger transaction. $I_j^{Treated}$ is an indicator function equal to one for employees in target firms, and equal to zero for employees in control firms. Standard errors are clustered at the transaction level. The sample period is from 2002 to 2017.
Significance Levels: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

**Table 5: M&As and Technological Change**

| | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| **Panel A: Technology Adoption and Innovation** | | | | | | |
| | **Innovation-Intensive Occupations** | | **Professional Occupations** | | **Blue-Collar Occupations** | |
| **Variables** | **Involuntary Separation {0,1}** | **Hired {0,1}** | **Involuntary {0,1}** | **Hired {0,1}** | **Involuntary Separation {0,1}** | **Hired {0,1}** |
| Post $\times$ $I_j^{Treated} \times I_j^C$ | -0.020** | 0.022** | -0.028*** | 0.052*** | 0.041*** | -0.025** |
| | (0.010) | (0.011) | (0.010) | (0.014) | (0.012) | (0.012) |
| Employee Controls | Yes | Yes | Yes | Yes | Yes | Yes |
| Firm FE | Yes | Yes | Yes | Yes | Yes | Yes |
| Year FE | Yes | Yes | Yes | Yes | Yes | Yes |
| Event Year FE | Yes | Yes | Yes | Yes | Yes | Yes |
| $R^2$ | 0.08 | 0.22 | 0.08 | 0.22 | 0.08 | 0.22 |
| Observations | 29,817,643 | 29,817,643 | 29,817,643 | 29,817,643 | 29,817,643 | 29,817,643 |
| **Panel B: Routine Task Intensity and IT Investment** | | | | | | |
| | **Routine Occupations** | | **IT Occupations** | | **IT-Enabled Occupations** | |
| **Variables** | **Involuntary Separation {0,1}** | **Hired {0,1}** | **Involuntary Separation {0,1}** | **Hired {0,1}** | **Involuntary Separation {0,1}** | **Hired {0,1}** |
| Post $\times$ $I_j^{Treated} \times I_j^C$ | 0.027*** | -0.029** | -0.034*** | 0.041** | -0.026** | 0.022** |
| | (0.009) | (0.012) | (0.012) | (0.017) | (0.011) | (0.010) |
| Employee Controls | Yes | Yes | Yes | Yes | Yes | Yes |
| Firm FE | Yes | Yes | Yes | Yes | Yes | Yes |
| Year FE | Yes | Yes | Yes | Yes | Yes | Yes |
| Event Year FE | Yes | Yes | Yes | Yes | Yes | Yes |
| $R^2$ | 0.08 | 0.22 | 0.08 | 0.22 | 0.08 | 0.22 |
| Observations | 29,817,643 | 29,817,643 | 29,817,643 | 29,817,643 | 29,817,643 | 29,817,643 |

**Notes:** The table reports estimates from Equation (7) for the sample of employees in target and control firms. In Columns (1), (3) and (5) the dependent variable is an indicator variable that is equal to one in the year when an involuntary separation occurs, whereas in Columns (2), (4) and (6) the dependent variable is an indicator variable that is equal to one in the year when the employee is hired. $I_j^C$ is an indicator function equal to one (i) for employees in innovation-intensive occupations in Columns (1) and (2) of Panel A, (ii) for employees in professional occupations in Columns (3) and (4) of Panel A, (iii) for employees in blue-collar occupations in Columns (5) and (6) of Panel A, (iv) for employees in routine occupations in Columns (1) and (2) of Panel B, (v) for employees in IT occupations in Columns (3) and (4) of Panel B, and (vi) for employees in IT-enabled occupations in Columns (5) and (6) of Panel B. *Post* is an indicator variable that equals one for the five-year period after the merger transaction, and zero for the two-year period prior to the merger transaction. $I_j^{Treated}$ is an indicator function equal to one for employees in target firms, and equal to zero for employees in control firms. Standard errors are clustered at the transaction level. The sample period is from 2002 to 2017.
Significance Levels: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

**Table 6: M&As and Organizational Streamlining**

| | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| **Panel A: Occupational Proximity and Overlap** | | | | | | |
| | **Total Sample** | | | | **Focused** | **Diversifying** |
| | **Occupational Proximity** | | **Occupational Overlap** | | **Occupational Overlap** | |
| **Variables** | **Involuntary Separation {0,1}** | **Hired {0,1}** | **Involuntary Separation {0,1}** | **Hired {0,1}** | **Involuntary Separation {0,1}** | **Involuntary Separation {0,1}** |
| Post $\times$ $I_j^{Treated} \times I_j^{Overlap}$ | 0.052*** | 0.005 | 0.020** | -0.018 | 0.025** | 0.005 |
| | (0.019) | (0.034) | (0.010) | (0.015) | (0.011) | (0.035) |
| $R^2$ | 0.09 | 0.22 | 0.09 | 0.22 | 0.09 | 0.09 |
| Observations | 20,141,320 | 20,141,320 | 20,141,320 | 20,141,320 | 17,094,137 | 3,043,080 |
| **Panel B: Managerial Occupations** | | | | | | |
| | **Managers (t = 0)** | **Managers** | **Supervisors (t = 0)** | **Supervisors** | **Clerical Support** | |
| **Variables** | **Involuntary Separation {0,1}** | **Hired {0,1}** | **Involuntary Separation {0,1}** | **Hired {0,1}** | **Involuntary Separation {0,1}** | **Hired {0,1}** |
| Post $\times$ $I_j^{Treated} \times I_j^{C}$ | 0.063*** | 0.064*** | -0.012* | 0.026** | -0.012 | -0.014 |
| | (0.011) | (0.014) | (0.007) | (0.012) | (0.015) | (0.013) |
| $R^2$ | 0.13 | 0.22 | 0.13 | 0.22 | 0.08 | 0.22 |
| Observations | 15,486,452 | 29,817,643 | 15,486,452 | 29,817,643 | 29,817,643 | 29,817,643 |
| Employee Controls | Yes | Yes | Yes | Yes | Yes | Yes |
| Event Year FE | Yes | Yes | Yes | Yes | Yes | Yes |
| Firm FE | Yes | Yes | Yes | Yes | Yes | Yes |
| Year FE | Yes | Yes | Yes | Yes | Yes | Yes |

**Notes:** The table reports estimates from Equation (7) for the sample of employees in target and control firms for mergers where information on the acquirer's occupational profile is available in RAIS. In Columns (1), (3), (5) and (6) of Panel A and Columns (1), (3) and (5) of Panel B the dependent variable is an indicator variable that is equal to one in the year when an involuntary separation occurs, whereas in Columns (2) and (4) of Panel A and Columns (2), (4) and (6) of Panel B the dependent variable is an indicator variable that is equal to one in the year when the employee is hired. Column (5) of Panel A restricts the sample to focused mergers, whereas Column (6) of Panel A focuses on diversifying mergers. Columns (1) and (3) of Panel B restrict the sample to employees present in the firm at the time of the merger. $I_j^{Overlap}$ is an indicator function equal to one (i) for employees in mergers where the *Occupational Proximity* variable has a value greater than the median value in Columns (1) and (2), and (ii) for employees in occupations that overlap with the acquirer in Columns (3) to (6). $I_j^{C}$ is an indicator function equal to one (i) for managers in Columns (1) and (2) of Panel B, (ii) for supervisors in Columns (3) and (4) of Panel B, and (iii) for employees in clerical support occupations in Columns (5) and (6) of Panel B. *Post* is an indicator variable that equals one for the five-year period after the merger transaction, and zero for the two-year period prior to the merger transaction. $I_j^{Treated}$ is an indicator function equal to one for employees in target firms, and equal to zero for employees in control firms. Standard errors are clustered at the transaction level. The sample period is from 2002 to 2017.
Significance Levels: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

**Table 7: Knowledge Transfer**

| | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| **Panel A: Acquirer-Target Distance** | | | | | | |
| **Variables** | **High-Skilled Share** | | **Routine Share** | | **Innovation-Intensive Share** | |
| | **High ΔSkill Share** | **Low ΔSkill Share** | **High ΔNon-Routine Share** | **Low ΔNon-Routine Share** | **High ΔInnovative Share** | **Low ΔInnovative Share** |
| Post $\times I_i^{Treated}$ | 0.031*** | -0.010 | -0.057*** | 0.015 | 0.017*** | 0.005 |
| | (0.008) | (0.008) | (0.011) | (0.010) | (0.006) | (0.004) |
| $R^2$ | 0.90 | 0.92 | 0.83 | 0.84 | 0.92 | 0.91 |
| Observations | 6,713 | 6,687 | 6,720 | 6,698 | 6,787 | 6,655 |
| **Panel B: Acquirer's Pre-Merger Shares** | | | | | | |
| **Variables** | **High-Skilled Share** | | **Routine Share** | | **Innovation-Intensive Share** | |
| | **High-Skilled Acquirer** | **Low-Skilled Acquirer** | **High Non-Routine Acquirer** | **Low Non-Routine Acquirer** | **High-Innovative Acquirer** | **Low-Innovative Acquirer** |
| Post $\times I_i^{Treated}$ | 0.025*** | 0.003 | -0.033*** | 0.001 | 0.018*** | 0.006 |
| | (0.008) | (0.006) | (0.012) | (0.009) | (0.006) | (0.004) |
| $R^2$ | 0.92 | 0.90 | 0.83 | 0.84 | 0.92 | 0.91 |
| Observations | 6,455 | 6,928 | 6,618 | 6,707 | 6,629 | 6,695 |
| Event Year FE | Yes | Yes | Yes | Yes | Yes | Yes |
| Firm FE | Yes | Yes | Yes | Yes | Yes | Yes |
| Year FE | Yes | Yes | Yes | Yes | Yes | Yes |

**Notes:** The table reports estimates from Equation (5). In Columns (1) and (2) the dependent variable is the share of high-skilled employees. In Columns (3) and (4) the dependent variable is the share of routine employees, whereas in Columns (5) and (6) the dependent variable is the share of innovation-intensive employees. *Post* is an indicator variable that equals one for the five-year period after the merger, and zero for the two-year period prior to the merger transaction. $I_i^{Treated}$ is an indicator function equal to one for target firms, and equal to zero for control firms that have never been involved in a merger transaction either as targets or acquirers during the period under study. In Panel A, Columns (1) and (2) report estimates for the subsample of merger transactions for which the difference in high-skilled share between the acquirer and the target at the year prior to the merger is in the top and bottom tercile, respectively. Columns (3) and (4) of Panel A report estimates for the subsample of merger transactions for which the difference in non-routine share between the acquirer and the target is in the top and bottom tercile, respectively. Columns (5) and (6) of Panel A report estimates for the subsample of merger transactions for which the difference in innovation-intensive share between the acquirer and the target is in the top and bottom tercile, respectively. In Panel B, Columns (1) and (2) report estimates for the subsample of mergers for which the acquirer's high-skilled share at the year prior to the merger is in the top and bottom tercile, respectively. Columns (3) and (4) report estimates for the subsample of mergers for which the acquirer's non-routine share at the year prior to the merger is in the top and bottom tercile, respectively. Columns (5) and (6) report estimates for the subsample of mergers for which the acquirer's innovation-intensive share at the year prior to the merger is in the top and bottom tercile, respectively. Standard errors are clustered at the transaction level. The sample period is from 2002 to 2017.
Significance Levels: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

**Table 8: Management Changes**

| | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| **Panel A: New CEO, CTO, CRO** | | | | | | |
| **Variables** | **High-Skilled Share** | | **Routine Share** | | **Innovation-Intensive Share** | |
| | **Hired CEO/CTO/CRO = 1** | **Hired CEO/CTO/CRO = 0** | **Hired CEO/CTO/CRO = 1** | **Hired CEO/CTO/CRO = 0** | **Hired CEO/CTO/CRO = 1** | **Hired CEO/CTO/CRO = 0** |
| Post $\times I_i^{Treated}$ | 0.016*** | 0.019*** | -0.027*** | -0.008 | 0.012*** | 0.002 |
| | (0.004) | (0.005) | (0.006) | (0.006) | (0.003) | (0.003) |
| $R^2$ | 0.95 | 0.92 | 0.88 | 0.84 | 0.94 | 0.90 |
| Observations | 14,130 | 16,511 | 14,130 | 16,511 | 14,129 | 16,496 |
| **Panel B: Manager Transfer from Acquirer to Target** | | | | | | |
| **Variables** | **High-Skilled Share** | | **Routine Share** | | **Innovation-Intensive Share** | |
| | **Transfer = 1** | **Transfer = 0** | **Transfer = 1** | **Transfer = 0** | **Transfer = 1** | **Transfer = 0** |
| Post $\times I_i^{Treated}$ | 0.023*** | 0.008 | -0.021*** | -0.014** | 0.010*** | 0.005** |
| | (0.004) | (0.006) | (0.005) | (0.007) | (0.004) | (0.002) |
| $R^2$ | 0.93 | 0.93 | 0.87 | 0.85 | 0.92 | 0.92 |
| Observations | 15,821 | 14,820 | 15,821 | 14,820 | 15,815 | 14,815 |
| Event Year FE | Yes | Yes | Yes | Yes | Yes | Yes |
| Firm FE | Yes | Yes | Yes | Yes | Yes | Yes |
| Year FE | Yes | Yes | Yes | Yes | Yes | Yes |

**Notes:** The table reports estimates from Equation (5). The dependent variable is the share of high-skilled employees in Columns (1) and (2); the share of routine employees in Columns (3) and (4); the share of innovation-intensive employees in Columns (5) and (6). *Post* is an indicator variable that equals one for the five-year period after the merger, and zero for the two-year period prior to the merger transaction. $I_i^{Treated}$ is an indicator function equal to one for target firms, and equal to zero for control firms that have never been involved in a merger transaction either as targets or acquirers during the period under study. Panel A report estimates for subsamples of merger transactions based on whether the target firm hires a CEO, CTO or CRO in the post-merger period. Panel B report estimates for subsamples of merger transactions based on whether the acquirer transfers an insider manager to the target firm. Standard errors are clustered at the transaction level. The sample period is from 2002 to 2017. Significance Levels: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

**Table 9: Fixed Costs of Technological Upgrade**

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| **Panel A: Occupational Overlap and Technological Upgrade** | | | | |
| **Variables** | **Involuntary Separation** | | | |
| | **Knowledge-Intensive Occupations = 0** | **Knowledge-Intensive Occupations = 1** | **Routine Occupations = 1** | **Routine Occupations = 0** |
| Post $\times$ $I_j^{Treated} \times I_j^{Overlap}$ | 0.023** | 0.012 | 0.027** | 0.005 |
| | (0.012) | (0.007) | (0.013) | (0.024) |
| Employee Controls | Yes | Yes | Yes | Yes |
| Event Year FE | Yes | Yes | Yes | Yes |
| Firm FE | Yes | Yes | Yes | Yes |
| Year FE | Yes | Yes | Yes | Yes |
| $R^2$ | 0.09 | 0.05 | 0.08 | 0.14 |
| Observations | 17,033,108 | 3,108,202 | 14,610,808 | 5,530,508 |
| **Panel B: Financial Constraints** | | | | |
| **Variables** | **High-Skill Share** | | **Routine Share** | |
| | **Small Firms** | **Large Firms** | **Small Firms** | **Large Firms** |
| Post $\times I_i^{Treated}$ | 0.038*** | 0.003 | -0.026*** | -0.009 |
| | (0.008) | (0.003) | (0.010) | (0.006) |
| Event Year FE | Yes | Yes | Yes | Yes |
| Firm FE | Yes | Yes | Yes | Yes |
| Year FE | Yes | Yes | Yes | Yes |
| $R^2$ | 0.90 | 0.96 | 0.80 | 0.90 |
| Observations | 9,833 | 10,537 | 9,833 | 10,537 |

**Notes:** Panel A reports estimates from Equation (7) for the sample of employees in target and control firms for mergers where information on the acquirer's occupational profile is available in RAIS. The dependent variable is an indicator variable that is equal to one in the year when an involuntary separation occurs. Columns (1) and (2) of Panel A report estimates for subsamples of employees based on whether the employee performs a knowledge-intensive occupation. Columns (3) and (4) of Panel A report estimates for subsamples of employees based on whether the employee performs a routine occupation. $I_j^{Overlap}$ is an indicator function equal to one for employees in occupations that overlap with the acquirer. $I_j^{Treated}$ is an indicator function equal to one for employees in target firms, and equal to zero for employees in control firms. Panel B reports estimates from Equation (5) for the sample of target firms and their controls. In Columns (1) and (2) the dependent variable is the share of high-skill employees, while in Columns (3) and (4) the dependent variable is the share of routine employees. *Post* is an indicator variable that equals one for the five-year period after the merger, and zero for the two-year period prior to the merger transaction. $I_i^{Treated}$ is an indicator function equal to one for target firms, and equal to zero for control firms. Columns (1) and (3) of Panel B report estimates for the subsample of mergers where the target firm is in the bottom tercile in terms of size. Columns (2) and (4) of Panel B report estimates for subsample of mergers where the target is in the top tercile in terms of size. Standard errors are clustered at the transaction level. The sample period is from 2002 to 2017.
Significance Levels: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

**Table 10: Acquirer-Target Convergence and Productivity**

| | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| **Panel A: Acquirer-Target Convergence** | | | | | | |
| | **Skill Composition** | | | **Routine Composition** | | |
| **Variables** | **ΔEducation Years** | **ΔPerson Fixed Effects** | **ΔSkilled Share** | **ΔRTI** | **ΔRoutine Share** | **ΔInnovation Share** |
| Post | -0.073*** | -0.008*** | -0.015*** | -0.067*** | -0.018*** | -0.006* |
| | (0.024) | (0.003) | (0.004) | (0.022) | (0.004) | (0.003) |
| Firm FE | Yes | Yes | Yes | Yes | Yes | Yes |
| Year FE | Yes | Yes | Yes | Yes | Yes | Yes |
| $R^2$ | 0.73 | 0.71 | 0.73 | 0.57 | 0.60 | 0.72 |
| Observations | 11,373 | 11,364 | 11,373 | 11,373 | 11,373 | 11,373 |
| **Panel B: Productivity** | | | | | | |
| | **AKM** | **Patents (OLS)** | | | **Patents (Count Models)** | |
| **Variables** | **AKM Firm Fixed Effects** | **Patent {0,1}** | **New Inventor {0,1}** | **Log (1+Patents)** | **Patent Count (NB)** | **Patent Count (Poisson)** |
| Post × $I_j^{Treated}$ | 0.021*** | 0.049*** | | 0.013** | 0.265* | 0.367* |
| | (0.006) | (0.010) | | (0.006) | (0.152) | (0.193) |
| $I_j^{Treated}$ | | | 0.031*** | | | |
| | | | (0.008) | | | |
| Event Year FE | Yes | Yes | Yes | Yes | Yes | Yes |
| Firm FE | Yes | Yes | Yes | Yes | Yes | Yes |
| Year FE | No | No | Yes | Yes | Yes | Yes |
| $R^2$ | 0.61 | 0.42 | 0.55 | 0.57 | 0.64 | 0.78 |
| Observations | 7,652 | 8,904 | 4,468 | 30,630 | 3,119 | 3,119 |

**Notes:** Panel A reports estimates from estimating 9 on the sample of target firms. *Post* is an indicator variable that equals one for the five-year period after the merger, and zero for the two-year period prior to the merger. The dependent variable is the distance in the years of education between acquirers and target firms in Column (1) of Panel A; the distance in person fixed effects between acquirers and target firms in Column (2) of Panel A; the distance in the share of high-skilled employees between acquirers and target firms in Column (3) of Panel A; the distance in routine task intensity between acquirers and target firms in Column (4) of Panel A; the distance in the share of routine employees between acquirers and target firms in Column (5) of Panel A; the distance in the share of innovation-intensive employees between acquirers and target firms in Column (6) of Panel A. Panel B reports estimates from Equation (5) for the sample of target firms and control firms. The dependent variable is the firm-level AKM firm fixed effect estimated for the six-year period before and after the merger in Column (1) of Panel B; an indicator variable that is equal to one in the years where a firm generates a patent in Column (2) of Panel B; an indicator variable that is equal to one if the firm generates a patent in the post-merger period in Column (3) of Panel B; the log of $1 + Patents$ in Column (4) of Panel B; the count of patents in Columns (5) and (6) of Panel B. $I_i^{Treated}$ is an indicator function equal to one for target firms, and equal to zero for control firms. Standard errors are clustered at the transaction level. The sample period is from 2002 to 2017. Significance Levels: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

# Appendix

## A AKM Methodology

To identify the employee and firm fixed effects, the AKM specification requires the presence of employees who switch firms in matched employer-employee datasets. In the absence of movers, separating employee effects from firm effects would be improbable. Yet, the presence of movers does not guarantee identification of all fixed effects. AKM provides an algorithm that exploits mobility to construct sets of firms and employees whose fixed effects are identifiable (the "connected set"). In the cohort-based six-year rolling-window AKM models that I estimate in RAIS, the largest connected set includes from 97% to 99% of the sample; therefore, restricting attention to the largest group of the sample is not a significant limitation.

To apply the AKM methodology to RAIS data, I follow Lopes de Melo (2018) and restrict my focus to full-time employees. To account for informality effects, I exclude individuals with available information for less than two out of the six years, and who have been employed in more than three firms per year. The estimated pre-merger person fixed effects are in turn assigned to employer-employee observations as a measure of employee skill.

An important concern with the AKM methodology is the potential existence of a "limited mobility bias" (e.g., Andrews et al., 2012), which implies the extent of mobility is an important determinant of the AKM being an unbiased estimator of employer fixed effects. Nevertheless, two features in the RAIS dataset suggest limited mobility is unlikely to be a concern for my estimates. First, the average number of movers per employer in my sample is about 17, whereas Andrews et al. (2012) demonstrates that limited mobility bias is likely to be a concern if the average number of movers per employer is less than six. Second, the rate of mobility is pretty high in RAIS, ranging from 13% to 18% depending on the time period under consideration.

Another significant concern with the AKM methodology is the validity of the exogenous mobility assumption which basically implies the assignment of employees to firms is uncorrelated with the error term.[31] To alleviate concerns regarding sorting and the significance of endogenous mobility in my estimations, I follow Card et al. (2013) and develop an event-study analysis that focuses on wage changes experienced by employees who transition across different groups of firms. Firms are grouped into quartiles based on the average wage of co-workers. In the absence of endogenous mobility, employees who switch from high-quartile firms to low-quartile firms should experience, on average, a decline in their wage level, whereas employees who move from low-quartile firms to high-quartile firms should experience, on average, an increase in their wage level.

Specifically, I begin by classifying firms into quartiles based on the average wage of co-workers. Then, for each year, I select employees with a tenure of at least two years at a specific firm who move to a different firm in the next period and remain with the subsequent firm for at least two years. Finally, for each combination of interquartile moves, I estimate the average log wage for the two-year period before and after the move. Indeed, Figure A1 demonstrates that employees who move from high-quartile firms to low-quartile firms experience, on average, a decline in their wage level, and employees who move from low-

[31] See the discussion in Card et al. (2013) and Card et al. (2018) for the assumptions necessary to lead to an unbiased estimation of employer fixed effects in the AKM specification.

quartile firms to high-quartile firms experience an increase in their wage level. In addition, the effect appears to be symmetric in the sense that wage changes reflect the fact that the AKM specification captures the additive effects of firm- and worker-level premiums.

## B Figures

**Figure A1:** AKM Exogenous Mobility Assumption

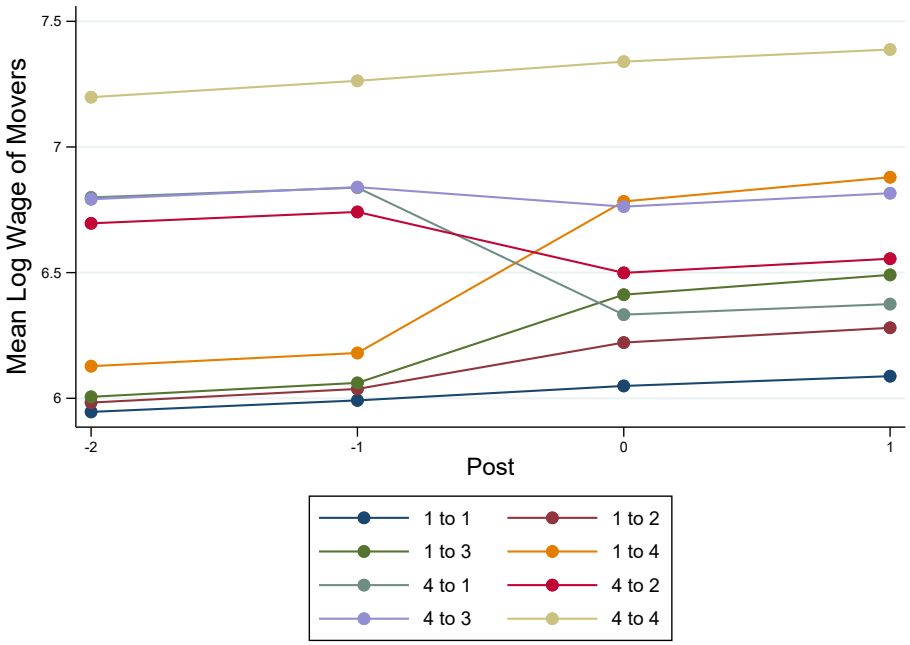
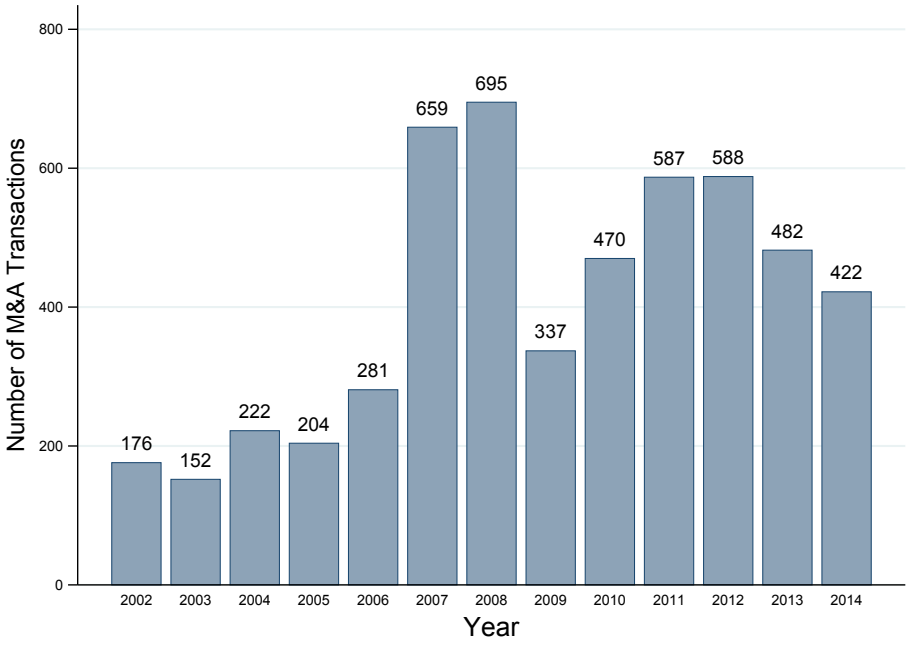



**Figure A2:** Publicly Announced and Completed Mergers in Brazil, Including Majority and Minority Stake Acquisitions. Source: Thomson SDC



## C Tables

**Table A1: Input-Based Measures of Technology Adoption and Innovation**

| **Panel A: Innovation-Intensive Occupations** | |
|---|---|
| **Keywords in Portuguese** | **Keywords in English** |
| Pesquisa e Desenvolvimento / P&D | Research and Development / R&D |
| Pesquisador | Researcher |
| Pesquisas Tecnologicas | Technological Research |
| Inovação | Innovation |
| Protótipos | Prototypes |
| Desenvolvimento de Produtos / Processos | Product / Process Development |
| Automaçao de Processos | Process Automation |
| Desenvolvem Produtos / Processos | Develop Products / Processes |
| Desenvolvem Pesquisas | Develop Research |
| Desenvolvem Equipamentos | Develop Equipment |
| Desenvolvem Dispositivos | Develop Devices |
| Otimizam Métodos | Optimize Methods |
| Otimizam os Meios | Optimize Means |
| Aperfeiçoam Sistemas | Improve Systems |
| Aperfeiçoam Dispositivos | Improve Devices |
| Aperfeiçoam Produtos / Processos | Improve Products / Processes |
| Implementam Dispositivos de Automaçao | Implement Automation Devices |
| Desenvolvem, Testam e Supervisionam Sistemas, Processos e Métodos Produtivos | Develop, Test and Supervise Systems, Processes and Production Methods |
| Novas Tecnologias | New Technologies |
| Produto(s) Novo(s) / Novo(s) Produto(s) | New Product(s) |
| Processo(s) Novo(s) / Novo(s) Processo(s) | New Process(es) |
| Produto(s) / Processo(s) Aprimorado(s) | Improved Product(s) / Process(es) |
| Inovação de Produto / Processo | Product / Process Innovation |
| Aperfeiçoamento de Produto / Processo | Product / Process Improvement |
| **Panel B: IT-Enabled and IT-Aided Occupations** | |
| **Keywords in Portuguese** | **Keywords in English** |
| Desenvolvem Sistemas | Develop Systems |
| Desenvolvem Aplicações | Develop Applications |
| Implementam Sistemas | Implement Systems |
| Implementam Aplicações | Implement Applications |
| Projetam Sistemas | Design Systems |
| Projetam Aplicações | Design Applications |
| Analisar Dados | Analyze Data |
| Sistemas Computacionais / Computação | Computational / Computing Systems |
| Equipamentos Computacionais | Computational Equipment |
| Programas Computacionais | Computational Programs |
| Ambientes Computacionais / Ambiente Computacional | Computational Environment(s) |
| Recursos Computacionais | Computational Resources |
| Sistemas (da) Informação / Informações / Informatizados | Information / Computerized Systems |
| Tecnologia (da) Informação / Tecnologias (de) Informática | Information Technology |
| Equipamentos (da) Informação / Equipamentos (de) Informática | Computer Equipment |
| Recursos (de) Informática | Computer Resources |
| Codificação / Codificando Programas | Coding Programs |
| Codificação / Codificando Dados | Coding Data |
| Codificação / Codificando Aplicações | Coding Applications |
| Interface Gráfica | Graphic Interface |
| Banco de Dados | Database |
| Software / Hardware | Software / Hardware |
| Suporte Técnico | Technical Support |
| Computador / Microcomputador / Laptop / Perifericos | Computer / Laptop / Peripherals |

**Notes:** The table reports the keywords in Portuguese used to identify innovation-intensive (Panel A) and IT-enabled (Panel B) occupations and their English translation.

**Table A2: Supervisors**

| Keywords in Portuguese | Keywords in English |
|---|---|
| Supervisionam Equipe(s) | Supervise Team(s) |
| Supervisionam Profissionais | Supervise Professionals |
| Supervisionam Rotina(s) | Supervise Routine(s) |
| Supervisionam Atividade(s) | Supervise Activity(ies) |
| Monitoram Equipe(s) | Monitor Team(s) |
| Monitoram Profissionais | Monitor Professionals |
| Monitoram Rotina(s) | Monitor Routine(s) |
| Monitoram Processos | Monitoram Processes |
| Controlam Equipe(s) | Control Team(s) |
| Controlam Rotina(s) | Control Routine(s) |
| Controlam Processos | Control Processes |
| Orientam Equipe(s) | Guide Team(s) |
| Orientam Profissionais | Guide Professionals |
| Motivam Equipe(s) | Motivate Team(s) |
| Motivam Profissionais | Motivate Professionals |
| Dirigem Equipe(s) | Direct Team(s) |
| Dirigem Profissionais | Direct Professionals |
| Avaliam Equipe(s) | Evaluate Team(s) |
| Avaliam Profissionais | Evaluate Professionals |
| Recrutam Equipe(s) | Recruit Team(s) |
| Recrutam Profissionais | Recruit Professionals |
| Treinam Equipe(s) | Train Team(s) |
| Treinam Profissionais | Train Professionals |
| Apresentam à Gerência | Present to Management |
| Formam Equipe(s) | Form Team(s) |
| Analisam Projetos | Analyze Projects |
| Coordenam Planos | Coordinate Plans |
| Coordenam Equipe(s) | Coordinate Team(s) |
| Coordenam Profissionais | Coordinate Professionals |
| Coordenam Serviços | Coordinate Services |
| Coordenam Processos | Coordinate Processes |
| Coordenam Recursos Humanos | Coordinate Human Resources |
| Planejam Equipe(s) | Plan Team(s) |
| Planejam Rotina(s) de Trabalho | Plan Work Routine(s) |
| Administram Equipe(s) | Manage Team(s) |
| Administram Profissionais | Manage Professionals |
| Administram Recursos Humanos | Manage Human Resources |
| Administram Mão-de-obra | Manage Manpower |
| Administram Selecionando, Contratando e Demitindo Pessoal | Manage Selection, Hiring and Firing of Personnel |
| Administram Processos | Manage Processes |
| Gerenciam Equipe(s) | Manage Team(s) |
| Gerenciam Profissionais | Manage Professionals |
| Gerenciam Pessoas | Manage People |
| Definir Rotina(s) de Trabalho | Define Work Routine(s) |
| Realizam Gestão de Recursos Humanos | Perform Human Resources Management |
| Realizam Selecionando, Treinando e Orientando | Perform Selection, Training and Orientation |
| Identificar Prioridades | Identify Priorities |
| Participam das decisões | Participate in Decisions |
| Equipe(s) de Trabalho | Work Team(s) |

**Notes:** The table reports the keywords in Portuguese used to identify supervisors and their English translation.

**Table A3: Ex Post Treatment Effect Sample**
**Target Vs. Control Employee Characteristics at t = -1**

| | Target Employees | | | Control Employees | | |
|---|---|---|---|---|---|---|
| **Variables** | **Mean** | **SD** | **Median** | **Mean** | **SD** | **Median** |
| Years of Education | 11.52 | 3.31 | 12 | 11.15 | 3.66 | 12 |
| Monthly Average Wage (R$) | 1,086 | 1,798 | 587 | 1,062 | 1,869 | 582 |
| Log Monthly Average Wage | 6.53 | 0.91 | 6.38 | 6.51 | 0.93 | 6.37 |
| Age | 32.23 | 9.82 | 30 | 33.10 | 10.36 | 31 |
| Female | 0.33 | 0.47 | 0 | 0.29** | 0.46 | 0 |
| High-Skilled | 0.23 | 0.42 | 0 | 0.22 | 0.42 | 0 |
| Routine | 0.76 | 0.43 | 1 | 0.74 | 0.44 | 1 |
| Innovation-Intensive | 0.06 | 0.23 | 0 | 0.06 | 0.23 | 0 |
| Blue-Collar | 0.40 | 0.49 | 0 | 0.42 | 0.49 | 0 |
| Number of Employees | 1,944,494 | | | 1,770,530 | | |

**Notes:** The table reports summary statistics on human capital characteristics for target and control firms. The set of control firms is based on a propensity score matching estimator using firm-level observable characteristics as described in Section 5.1.1.
Significance Levels: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

**Table A4: Firm-Level Compositional Changes**

**Panel B: Firm-Level Compositional Changes**

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
|---|---|---|---|---|---|---|---|---|
| | Skill Upgrade | | | Routine-Biased Change | | Technological Change | | |
| **Variables** | **Years of Education** | **Person Fixed Effects** | **High-Skill Share** | **RTI** | **Routine Share** | **Innovation Share** | **IT Share** | **Knowledge-Intensive Share** |
| Post $\times I_i^{Treated}$ | 0.079*** | 0.014*** | 0.019*** | -0.059*** | -0.021*** | 0.007*** | 0.004** | 0.029*** |
| | (0.014) | (0.002) | (0.003) | (0.019) | (0.004) | (0.002) | (0.002) | (0.004) |
| Event Year FE | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Firm FE | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Year FE | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| $R^2$ | 0.95 | 0.93 | 0.94 | 0.84 | 0.89 | 0.92 | 0.94 | 0.93 |
| Observations | 30,630 | 30,596 | 30,630 | 30,630 | 30,630 | 30,630 | 30,630 | 30,630 |

**Panel B: Firm-Level Compositional Changes with Additional Fixed Effects**

| | Skill Upgrade | | | Routine-Biased Change | | Technological Change | | |
|---|---|---|---|---|---|---|---|---|
| **Variables** | **Years of Education** | **Person Fixed Effects** | **High-Skill Share** | **RTI** | **Routine Share** | **Innovation Share** | **IT Share** | **Knowledge-Intensive Share** |
| Post $\times I_i^{Treated}$ | 0.089*** | 0.015*** | 0.020*** | -0.051*** | -0.018*** | 0.006*** | 0.004** | 0.030*** |
| | (0.023) | (0.002) | (0.004) | (0.019) | (0.004) | (0.002) | (0.002) | (0.004) |
| Event Year FE | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Firm FE | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Sector × Year FE | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| $R^2$ | 0.95 | 0.93 | 0.94 | 0.84 | 0.89 | 0.92 | 0.94 | 0.93 |
| Observations | 30,630 | 30,596 | 30,630 | 30,630 | 30,630 | 30,630 | 30,630 | 30,630 |

**Notes:** The table reports estimates from Equation (5) for the sample of target and control firms. In Column (1) the dependent variable is the firm-level average of the years of education of the labor force. In Column (2) the dependent variable is the share of high-skilled employees. In Column (3) the dependent variable is the firm-level average AKM person fixed effect. In Column (4) the dependent variable is the firm-level average routine task intensity score. In Column (5) the dependent variable is the share of routine employees. In Column (6) the dependent variable is the share of employees in innovation-intensive occupations. In Column (7) the dependent variable is the share of IT employees. In Column (8) the dependent variable is the share of employees in knowledge-intensive occupations *Post* is an indicator variable that equals one for the five-year period after the merger, and zero for the two-year period prior to the merger. $I_i^{Treated}$ is an indicator function equal to one for target firms, and equal to zero for control firms. Standard errors are clustered at the transaction level. The sample period is from 2002 to 2017.
Significance Levels: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

**Table A5: Occupation Overlap - Acquirers**

| | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| | Total Sample | | | | Focused | Diversifying |
| | Occupational Proximity | | Occupational Overlap | | Occupational Overlap | |
| **Variables** | **Involuntary Separation {0,1}** | **Hired {0,1}** | **Involuntary Separation {0,1}** | **Hired {0,1}** | **Involuntary Separation {0,1}** | **Involuntary Separation {0,1}** |
| Post $\times$ $I_j^{Treated} \times I_j^{Overlap}$ | -0.001 | -0.002 | 0.006 | 0.011 | 0.007 | 0.014 |
| | (0.004) | (0.007) | (0.006) | (0.010) | (0.007) | (0.009) |
| Employee Controls | Yes | Yes | Yes | Yes | Yes | Yes |
| Event Year FE | Yes | Yes | Yes | Yes | Yes | Yes |
| Firm FE | Yes | Yes | Yes | Yes | Yes | Yes |
| Year FE | Yes | Yes | Yes | Yes | Yes | Yes |
| $R^2$ | 0.08 | 0.21 | 0.08 | 0.21 | 0.07 | 0.12 |
| Observations | 116,744,284 | 116,744,284 | 116,744,284 | 116,744,284 | 97,096,940 | 19,501,411 |

**Notes:** The table reports estimates from Equation (7) for the sample of employees in acquirers and control firms for mergers. In Columns (1), (3), (5) and (6) the dependent variable is an indicator variable that is equal to one at the year when an involuntary separation occurs, whereas in Columns (2) and (4) the dependent variable is an indicator variable that is equal to one at the year when the employee is hired. Column (5) restricts the sample to focused mergers, whereas Column (6) focuses on diversifying mergers. $I_j^{Overlap}$ is an indicator function equal to one (i) for employees in mergers where the *Occupational Proximity* variable has a value greater than the median value in Columns (1) and (2), and (ii) for employees in occupations that overlap with the target firm in Columns (3) to (6). *Post* is an indicator variable that equals one for the five-year period after the merger transaction, and zero for the two-year period prior to the merger transaction. $I_j^{Treated}$ is an indicator function equal to one for employees in acquirers, and equal to zero for employees in control firms. Standard errors are clustered at the transaction level. The sample period is from 2002 to 2017.
Significance Levels: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

**Table A6: Technology and Knowledge Transfer in Mergers with Foreign Acquirers**

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| **Variables** | **High-Skilled Share** | **Routine Share** | **Innovation-Intensive Share** | **Knowledge-Intensive Share** |
| Post $\times I_i^{Treated}$ | 0.025*** | -0.018*** | 0.006* | 0.032*** |
| | (0.005) | (0.005) | (0.003) | (0.005) |
| Event Year FE | Yes | Yes | Yes | Yes |
| Firm FE | Yes | Yes | Yes | Yes |
| Year FE | Yes | Yes | Yes | Yes |
| $R^2$ | 0.94 | 0.86 | 0.93 | 0.92 |
| Observations | 13,146 | 13,146 | 13,146 | 13,146 |

**Notes:** The table reports estimates from Equation (5) for the subsample of mergers with a foreign acquirer. The dependent variable is the share of high-skill employees in Column (1); the share of routine employees in Column (2); the share of innovation-intensive employees in Column (3); and the share of knowledge-intensive employees in Column (4). *Post* is an indicator variable that equals one for the five-year period after the merger, and zero for the two-year period prior to the merger transaction. $I_i^{Treated}$ is an indicator function equal to one for target firms, and equal to zero for control firms. Standard errors are clustered at the transaction level. The sample period is from 2002 to 2017.
Significance Levels: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

**Table A7: Mechanisms - Triple Interactions**

| | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| **Panel A: Knowledge Transfer** | | | | | | |
| | **Acquirer-Target Distance** | | | **Acquirer's Pre-Merger Share** | | |
| **Variables** | **Skill Intensity** | **Routine Intensity** | **Innovation Intensity** | **Skill Intensity** | **Routine Intensity** | **Innovation Intensity** |
| Post $\times I_i^{Treated}$ | -0.007 | 0.014 | 0.004 | 0.003 | 0.002 | 0.005 |
| | (0.008) | (0.010) | (0.004) | (0.006) | (0.009) | (0.004) |
| Post $\times I_i^{Treated} \times I_i^{High}$ | 0.036*** | -0.072*** | 0.013* | 0.023** | -0.035** | 0.014** |
| | (0.011) | (0.015) | (0.007) | (0.010) | (0.015) | (0.007) |
| $R^2$ | 0.91 | 0.84 | 0.92 | 0.94 | 0.85 | 0.92 |
| Observations | 13,394 | 13,418 | 13,442 | 13,383 | 13,325 | 13,324 |
| **Panel B: Management Changes** | | | | | | |
| | **New CEO, CTO, CRO** | | | **Manager Transfer from Acquirer to Target** | | |
| **Variables** | **Skill Intensity** | **Routine Intensity** | **Innovation Intensity** | **Skill Intensity** | **Routine Intensity** | **Innovation Intensity** |
| Post $\times I_i^{Treated}$ | 0.018*** | -0.009 | 0.002 | 0.008 | -0.015** | 0.005* |
| | (0.005) | (0.006) | (0.003) | (0.005) | (0.007) | (0.002) |
| Post $\times I_i^{Treated} \times I_i^{High}$ | -0.002 | -0.018** | 0.010** | 0.016** | -0.006 | 0.006 |
| | (0.006) | (0.008) | (0.004) | (0.006) | (0.009) | (0.004) |
| $R^2$ | 0.93 | 0.86 | 0.92 | 0.93 | 0.86 | 0.92 |
| Observations | 30,630 | 30,630 | 30,630 | 30,630 | 30,630 | 30,630 |
| Event Year FE | Yes | Yes | Yes | Yes | Yes | Yes |
| Firm FE | Yes | Yes | Yes | Yes | Yes | Yes |
| Year FE | Yes | Yes | Yes | Yes | Yes | Yes |

**Notes:** The table reports estimates from an extended triple difference version of Equation (5). In Columns (1) and (4) the dependent variable is the share of high-skilled employees. In Columns (2) and (5) the dependent variable is the share of routine employees, whereas in Columns (3) and (6) the dependent variable is the share of innovation-intensive employees. *Post* is an indicator variable that equals one for the five-year period after the merger, and zero for the two-year period prior to the merger transaction. $I_i^{Treated}$ is an indicator function equal to one for target firms, and equal to zero for control firms that have never been involved in a merger transaction either as targets or acquirers during the period under study. In Column (1) of Panel A, $I_i^{High}$ is equal to one for transactions for which the difference in high-skilled share between the acquirer and the target firm at the year prior to the merger is in the top tercile and zero in the bottom tercile, respectively. In Column (2) of Panel B, $I_i^{High}$ is equal to one for transactions for which the difference in non-routine share between the acquirer and the target firm at the year prior to the merger is in the top tercile and zero in the bottom tercile, respectively. In Column (3) of Panel B, $I_i^{High}$ is equal to one for transactions for which the difference in innovation-intensive share between the acquirer and the target firm at the year prior to the merger is in the top tercile and zero in the bottom tercile, respectively. In Column (1) of Panel B, $I_i^{High}$ is equal to one for transactions for which the acquirer's high-skilled share at the year prior to the merger is in the top tercile and zero in the bottom tercile, respectively. In Column (2) of Panel B, $I_i^{High}$ is equal to one for transactions for which the acquirer's non-routine share at the year prior to the merger is in the top tercile and zero in the bottom tercile, respectively. In Column (3) of Panel B, $I_i^{High}$ is equal to one for transactions for which the acquirer's innovation-intensive at the year prior to the merger is in the top tercile and zero in the bottom tercile, respectively. Standard errors are clustered at the transaction level. The sample period is from 2002 to 2017.
Significance Levels: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

**Table A8: Serial Acquirers**

| | (1) | (2) | (3) |
|---|---|---|---|
| **Variables** | **High-Skilled Share** | **Routine Share** | **Innovation-Intensive Share** |
| Post $\times$ $I_i^{Treated}$ | 0.023*** | -0.021*** | 0.005** |
| | (0.004) | (0.007) | (0.002) |
| Post $\times$ $I_i^{SerialAcquirer}$ | -0.001 | -0.007 | -0.001 |
| | (0.003) | (0.005) | (0.002) |
| Post $\times$ $I_i^{Treated}$ $\times$ $I_i^{SerialAcquirer}$ | -0.004 | -0.000 | 0.006 |
| | (0.008) | (0.010) | (0.004) |
| $R^2$ | 0.94 | 0.88 | 0.92 |
| Observations | 30,801 | 30,801 | 30,801 |
| Event Year FE | Yes | Yes | Yes |
| Firm FE | Yes | Yes | Yes |
| Year FE | Yes | Yes | Yes |

**Notes:** The table reports estimates from Equation (10) for the sample of target and control firms. The dependent variable is the share of high-skill employees in Column (1); the share of routine employees in Column (2); and the share of innovation-intensive employees in Column (3). *Post* is an indicator variable that equals one for the five-year period after the merger, and zero for the two-year period prior to the merger transaction. $I_i^{Treated}$ is an indicator function equal to one for target firms, and equal to zero for control firms. $I_i^{SerialAcquirer}$ is an indicator function equal to one in mergers where the acquirer engages in multiple acquisitions in our period under study, and zero otherwise. Standard errors are clustered at the transaction level. The sample period is from 2002 to 2017.
Significance Levels: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.