THREE ESSAYS ON LABOR MARKET DYNAMICS IN BRAZIL

by

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A DISSERTATION

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ABSTRACT

In the first essay, we use linked employer-employee data for the formal labor market in Brazil to examine the relative importance of firm age and firm size for job creation and destruction in Brazil. We find that firm age is a more important determinant of job creation in Brazil than is firm size; young firms and firm start-ups create a relatively high number of jobs in Brazil. We also find that young firms are more likely to exit the market and have higher levels of employment volatility. We, therefore, condition the job creation analysis on job stability and find that young firms and large firms create most of the stable jobs in Brazil.

In the second essay, I analyze the impact of a trade shock on gender-specific local labor market outcomes in Brazil. I use an instrumental variable approach and linked employer-employee data to estimate the effect of both increased imports from China and exports to China on labor market outcomes in Brazil. Exports to China increase female employment growth in both the traded sector and the non-traded sector. Increased trade with China also increases female wage growth in both sectors; however, this does not translate to any improvements in the average wage ratio.

In the third and final essay, we analyze the effect of the China trade shock on labor market reallocation and migration in Brazil. Microregions more exposed to exports to China experienced higher migration rates, but those more exposed to imports from China experienced lower migration rates. Additionally, workers employed in microregions more exposed to increased imports are: (1) less likely to transition from the traded sector to nonemployment, but (2) more likely to transition from nonemployment to the nontraded sector. However, we do not find many significant effects of export exposure on labor reallocation across industries or nonemployment.
DEDICATION

To my family, who have supported me from day one. Thank you for believing in me and for always encouraging me. To my mom, who has given me countless hours of advice and is always willing to share her wisdom. To my dad, who continues to surprise me with his patience and is always willing to listen. To my sister, Jennifer, who set the best example of how to finish a dissertation while also having a little fun.
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<th>Abbreviation</th>
<th>Description</th>
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<tbody>
<tr>
<td>HJM</td>
<td>Haltiwanger, Jarmin, and Miranda (2013)</td>
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<tr>
<td>OECD</td>
<td>Organization for Economic Co-operation and Development</td>
</tr>
<tr>
<td>RAIS</td>
<td>Relação Anual de Informações Sociais data set</td>
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<tr>
<td>G</td>
<td>Employment growth rate</td>
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<tr>
<td>E</td>
<td>Level of employment in December</td>
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<tr>
<td>WRR</td>
<td>Worker reallocation rate</td>
</tr>
<tr>
<td>A</td>
<td>Number of accessions</td>
</tr>
<tr>
<td>S</td>
<td>Number of separations</td>
</tr>
<tr>
<td>SR</td>
<td>Separation rate</td>
</tr>
<tr>
<td>SWT</td>
<td>Stable-worker tenure</td>
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<tr>
<td>SWR</td>
<td>Stable-worker retention</td>
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<tr>
<td>SFT</td>
<td>Stable-firm tenure</td>
</tr>
<tr>
<td>SFR</td>
<td>Stable-firm retention</td>
</tr>
<tr>
<td>SGT</td>
<td>Stable employment growth using tenure</td>
</tr>
<tr>
<td>SGR</td>
<td>Stable employment growth using retention</td>
</tr>
<tr>
<td>MTE</td>
<td>Ministerio do Trabalho e Emprego</td>
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<tr>
<td>WTO</td>
<td>World Trade Organization</td>
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<tr>
<td>GDP</td>
<td>Gross Domestic Product</td>
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<tr>
<td>ISI</td>
<td>Import substitution industrialization</td>
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<tr>
<td>ΔIPW</td>
<td>Change in Chinese import exposure per worker</td>
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<tr>
<td>L</td>
<td>Employment</td>
</tr>
<tr>
<td>ΔM</td>
<td>Change in imports (in USD)</td>
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<tr>
<td>ΔEPW</td>
<td>Change in Chinese export exposure per worker</td>
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</table>
\( \Delta E \quad \text{Change in exports (in USD)} \)

2SLS Two-stage least squares regression model

\( Y \) Outcome variables in regression models

\( \alpha \) Constant term in regression models

\( \beta \) Regression coefficient for \( \Delta IPW \)

\( \gamma \) Regression coefficient for \( \Delta EPW \)

\( X \) Vector of microregion-specific control variables

\( \lambda \) Regression coefficient for \( X \)

\( \epsilon \) Error term for regression models

\( G \) Gender component of the change in occupation segregation

\( O \) Occupation component of the change in occupation segregation

CPI Consumer price index

HS Harmonized Commodity and Coding System

ISIC International Standard Industrial Classification system

IGBE Brazilian Institute for Geography and Statistics

CNAE Brazil’s National Classification of Economic Activities system

CBO Brazilian Occupation Classification system

OLS Ordinary least squares regression model

\( m \) Proportion of all employed males

\( f \) Proportion of all employed females

\( q \) Percentage of males in a certain occupation

\( p \) Percentage of females in a certain occupation

\( T \) Total number of males and females in a certain occupation

emp. Employed
ACKNOWLEDGMENTS

A tremendous amount of this dissertation is due to the guidance and support of Dr. Peter Brummund. He is a wonderful advisor who helped guide me through the highs and lows of the research process, taught me how to think about the big questions, and encouraged me through the long process of the academic job market. My time working both for and with you has been a great experience during my time in graduate school. Thank you for pushing me when I needed to be pushed and for always being patient with me.

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CHAPTER 1

WHO CREATES STABLE JOBS? EVIDENCE FROM BRAZIL (WITH PETER BRUMMUND)

1.1 Introduction

The view that small businesses fuel job creation remains a popular belief in most developed and emerging economies. Early empirical research found an inverse relationship between firm growth rates and firm size (Birch, 1981). However, more recent research identified statistical issues with the earlier analyses and went on to show that firm age is a more important determinant of job creation than firm size (Davis, Haltiwanger, & Schuh, 1996a; Davidsson, Lindmark, & Olofsson, 1998; Ayyagari, Demirguc-Kunt, & Maksimovic, 2014). That is, young firms and start-ups contribute more to job creation than small firms in many advanced economies (Haltiwanger, Jarmin, & Miranda, 2013; Decker, Haltiwanger, Jarmin, & Miranda, 2014). However, young firms and firm start-ups are inherently volatile and exhibit relatively high employment turnover rates (Haltiwanger, Hyatt, McEntarfer, & Sousa, 2012). While that volatility is a natural part of business dynamics, it also provides a note of caution about job creation policies and programs. If policies designed to create jobs target young firms, it could lead to an increase in job turnover in the economy. While job turnover can help improve matches between a worker and their employer, it is also costly for both the worker and the firm (Jacobson, LaLonde, & Sullivan, 1993; Couch & Placzek, 2010; Davis & von Wachter, 2011). Therefore, it is worthwhile to further explore the role of firm age and firm size in employment growth to determine what types of firms create stable jobs.

In this paper, we analyze the relationship between firm characteristics and
employment dynamics in the context of an emerging economy, Brazil. We use a linked employer-employee data set for the formal labor market in Brazil for 2004 to 2013 and follow the methodology of Haltiwanger et al. (2013). A linked employer-employee data set is ideal for studying employment dynamics, particularly when conditioned on a measure of job stability, due to the ability to track workers, establishments, and firms across time. We aim to first document the role of firm size and firm age in job creation and job destruction in Brazil. Following Haltiwanger et al.’s (2013) methodology also allows us to compare our findings for Brazil to those for the United States. Then, we examine the relationship between firm size, firm age, and employment volatility in Brazil. Last, we condition the job creation analysis on a measure of job stability to identify what types of firms create stable jobs in Brazil.

We extend the literature in two primary ways. First, we document the relative importance of firm age and firm size in employment dynamics in Brazil. Most of the literature uses data from the United States or other developed countries (Davis et al., 1996a; Neumark, Wall, & Zhang, 2011; Haltiwanger et al., 2013; Criscuolo, Gal, & Menon, 2014). Criscuolo et al. (2014) include Brazil in their analysis, but their analysis of the relative importance of firm size and firm age is not country specific. Rather, the authors average across all 18 countries in their data. Second, we extend the job creation analysis to account for the stability of the jobs created. Previous studies on job creation do not account for job stability (Davis et al., 1996b; Haltiwanger et al., 2013; Criscuolo et al., 2014) and previous studies on job stability do not focus on firm characteristics (Diebold, Neumark, & Polsky, 1997; Marcotte, 1998; Heisz, 2005; Bergmann & Mertens, 2011).

Job creation and stability are especially important in an emerging economy like Brazil because formal sector jobs provide a steady source of good income, serve as a primary pathway out of poverty, and provide access to legally mandated rights and benefits for workers (Dix-Carneiro & Kovak, 2017). It is also reasonable to expect that job stability is even more important for workers in emerging economies as these workers often do not
have access to generous safety nets and job loss could have serious negative consequences for workers and their families. Employment turnover and job stability are also current policy concerns in Brazil. Brazil has several policies aimed at reducing employment turnover, such as severance payment programs and taxes assessed on firms with high turnover rates (Gonzaga, Maloney, & Mizala, 2013; “The 50-year Snooze”, 2014). However, Brazil’s current policies address employment turnover and low job stability after the fact. A more thorough understanding of what types of firms create stable jobs will help create better-informed policies that can proactively address high employment turnover and low levels of job stability.

The first part of the project documents the relative importance of firm size and firm age in job creation and destruction in Brazil. The results show that young, small firms play a large role in employment, job creation, and job destruction in Brazil. This is consistent with Criscuolo et al.’s (2014) findings. They show that Brazil is unique from the OECD countries studied in the importance of young firms. We also find that firm age is a more important determinant of job creation in Brazil than firm size, but young firms are also more likely to exit the market. This is consistent with findings for the US (Haltiwanger et al., 2013) and the average across the countries studied in (Criscuolo et al., 2014).

Next, we analyze the relationship between firm size, firm age, and employment volatility. We use both a worker reallocation rate and a separation rate to measure employment volatility. For both measures, we find that young firms in Brazil exhibit higher levels of employment turnover relative to older firms. The third part of the project analyzes the relative importance of firm age and firm size in the creation of stable jobs in Brazil. The results show that both firm age and firm size are important determinants of stable employment growth. Young firms and large firms have relatively higher stable employment growth rates in comparison to older and smaller firms. While young firms have high levels of employment turnover, they are also an important generator of stable jobs in Brazil. Together, the results highlight the important role young firms and firm
start-ups play in Brazil’s economy.

The rest of the paper proceeds as follows. In section 2, we review the literature on job creation, job destruction, and job stability. Section 3 describes the methodology and Section 4 describes the data. Section 5 presents the main empirical results; section 5.1 analyzes job creation in Brazil, section 5.2 documents employment turnover, and section 5.3 identifies what types of firms create stable jobs. Finally, section 6 offers concluding remarks.

1.2 Literature Review

The common perception that small businesses contribute most to job creation in the United States was initially supported by most empirical work (Birch, 1981; Kirchoff & Phillips, 1988; Neumark et al., 2011). However, Brown, Hamilton, and Medoff (1990) argued that small firms only appeared important because the fastest growing industries had disproportionately more small firms. Similarly, Davis et al. (1996b) found that research often overestimated the results in favor of small firms. Further, most prominent studies that support the inverse relationship between employment growth and firm size analyzed only establishment-level or only firm-level data. Davis et al. (1996b) also emphasized the importance of using both establishment- and firm-level data to ensure employment dynamics are accurately captured. We use longitudinal linked employer-employee data that includes worker-, establishment- and firm-level data, which allows us to both properly analyze employment growth and extend the analysis to account for job stability.

More recent research focuses on the effects of both firm age and firm size in employment dynamics, often emphasizing the importance of young firms and firm start-ups. Haltiwanger et al. (2013) used the Census Bureau’s Longitudinal Business

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1This is due to the regression-to-the-mean bias inherent to using the base-year size methodology to classify firm size. In order to overcome this issue, the authors use the average size methodology, which averages firm size across years $t$ and $t-1$, to average out the serially uncorrelated measurement errors in firm size.
Database, which includes both establishment- and firm-level data, and convincingly showed that firm age is a more important determinant of job creation than firm size in the US. Their findings echoed the conclusion of Davidsson et al. (1998), who argued that firm age is likely a more important determinant of employment growth, noting that new firms are also relatively small in size. Decker et al. (2014) analyze the importance of entrepreneurship in job creation and employment dynamics using both establishment- and firm-level data. They show start-ups and small businesses are very important contributors to job creation in the US, but their contribution has declined over the last 30 years. While most research focuses on the US or other developed countries, Ayyagari et al. (2014) investigate what types of establishments create jobs in developing countries. Their results show that small, young establishments (less than 20 employees and at least 5 years old) contributed most to job creation in the selected developing countries.

The OECD has undertaken an impressive effort to build a collection of firm-level data on employment dynamics from 18 countries. Brazil is the only country in the collection that is not a member of the OECD. Criscuolo et al. (2014) use the data to document the dynamics of employment growth and how the Great Recession impacted those dynamics. The report shows that, on average across all 18 countries, firm age is a more important determinant of job creation than firm size. However, the relative contribution of firm age and firm size is not formally analyzed for each country independently. Since Brazil is the only non-OECD country in the dataset, their findings may mask a heterogenous result for Brazil. We examine this in the first section of our analysis.

Numerous studies exist which examine the relationship between firm size and employment growth, and later studies often control for firm age. However, the literature is lacking an analysis of job creation and employment growth conditioned on job stability. While Kirchoff and Phillips (1988) found small firms account for over 50% of net new jobs, they also found small firms account for over 50% of jobs lost from firm exit. This highlights
the volatile nature of firm start-ups and young firms. Davis et al. (1996b) pointed out that almost all analytic studies on the role of small firms in job creation ignore the durability of a job. This is a real policy concern since it is well documented that large firms have lower employment turnover rates (Brown & Medoff, 1989; Brown et al., 1990; Bergmann & Mertens, 2011; Haltiwanger, Hyatt, & McEntarfer, 2015).

Several studies analyze job stability at the worker level across time within a particular country. Bergmann and Mertens (2011) analyzed job stability trends in West Germany from 1984 to 1997, using the worker’s tenure to measure job stability. The authors found that job stability declined in Germany over the sample. Heisz (2005) conducted a similar analysis for job stability in Canada during the 1980’s and 1990’s, but used retention rates to measure job stability. The author determined that retention rates in Canada increased during periods of labor market slack but decreased during periods of labor market boom. Diebold et al. (1997) and Marcotte (1998) both analyzed worker-level job stability in the US during the 1980’s. Diebold et al. (1997) found that retention rates remained stable over the sample period. In contrast, Marcotte (1998) found that job stability declined for male head of households from 1976 to 1992.

Recent work often emphasizes the importance of business cycle dynamics in the analysis of employment growth and job stability. Cravo (2011) used aggregate job flow data at the establishment level and found that small establishments are more sensitive to business cycle dynamics than large establishments in Brazil. Moscarini and Postel-Vinay (2012) found that small firms matter most for job creation during times of high unemployment, but large firms matter most during times of low unemployment in the US. However, Haltiwnager, Hyatt, Kahn, and McEntarfer (2017) found no evidence that workers move up the firm size ladder, but rather move up the firm wage ladder in the U.S. Nagore García analyzed the stability of new job matches in Spain before and during the

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2Retention rates measure the probability that a worker with a particular level of tenure today will have an additional $k$ years of tenure $k$ years hence. A formal definition of retention rates is presented in Section 3.
financial crisis, using administrative worker-level data. The authors found a positive relationship between firm size and job stability for new job matches, which was stronger during the 2009 recession relative to before the crisis in 2005.

The majority of job stability research to date analyzes how job stability varies with worker characteristics and how job stability changes within a country over a given time period or across business cycles. The current literature lacks a study that analyzes firm characteristics and job creation conditioned on a measure of job stability. We attempt to fill this gap.

1.3 Methodology

We analyze the relative importance of firm age and firm size in various employment dynamics in Brazil. We follow Haltiwanger et al.’s (2013, hereafter HJM) empirical approach as closely as possible to be consistent with the literature. HJM use eight firm size classes (1-4, 5-9, 10-19, 20-49, 50-99, 100-249, 250-499, 500+) and nine firm age classes (0, 1-2, 3-4, 5-6, 7-8, 9-10, 11-12, 13-15, 16+) to estimate one-way and two-way models of job creation and destruction. Their methodology allows each size and age class to have a heterogeneous effect on employment dynamics. First, we estimate a series of one-way models to analyze employment dynamics by firm size class or firm age class only. Then, we estimate a series of two-way models to analyze employment dynamics by firm size class, firm age class, and all possible interactions. All models are also employment weighted. A comparison of the results from the one-way models with those from the two-way models easily shows the relationship between employment dynamics, firm size, and firm age, as well as the importance of accounting for firm age in the analysis.3

One-way models require one size class or one age class be omitted as a baseline comparison group. Following HJM, we omit the largest firm size class (500+ employees) or

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3We also conduct the analysis using industry and year controls. However, these results are extremely similar to our main analysis and therefore are included in the appendix.
the oldest firm age class (16+ years). The result for the omitted category is reported at its unconditional mean for each one-way model. Since the method focuses on the relative differences between size and age classes, the unconditional mean of the omitted group is added to the other estimates for each size and age class to re-scale them.

Given that some areas of the joint firm size and age distribution have relatively few observations, HJM limit the maximum size threshold to 500 employees and the maximum age threshold to 16 years. They also use two methods to measure firm size in their analysis since the base-year size methodology leads to regression-to-the-mean effects. Firm size and firm size classes are calculated once using the base-year size methodology and a second time using the average size methodology. The base-year size methodology calculates firm size for year $t$ as firm size in year $t$ for new firms and firm size in year $t-1$ for all other firms (both continuing and destroyed). The average size methodology calculates firm size for year $t$ as the average of firm size in year $t$ and year $t-1$ for all firms.\(^4\)

The main dependent variable in the job creation analysis is the employment growth rate, either at the establishment level or the firm level. An establishment is a single location where business is conducted (for example, a storefront) and a firm is the parent company with ownership over one or more establishments (for example, a retail corporate headquarters). The employment growth rate for establishment $i$ in year $t$, made popular by Davis, Haltiwanger, and Schuh (1996a), is calculated as follows:

$$G_{it} = \frac{E_{it} - E_{it-1}}{0.5 \times (E_{it} + E_{it-1})},$$

where $E_{it}$ is the level of employment for establishment $i$ in December of year $t$. The growth rate is symmetric around zero and bounded between -2 (destroyed establishments) and 2 (new establishments). Firm growth rates are then calculated as the employment-weighted average of the establishment growth rates under control of the firm. Thus, firm growth

\(^4\)We include formal definitions for all fundamental worker-level, establishment-level, and firm-level concepts used for the project in the appendix.
rates share the same properties as establishment growth rates.

The second part of the project analyzes employment volatility by firm size and firm age classes. Analyzing measures of employment volatility helps motivate the need to include a measure of job stability when analyzing employment growth. We capture employment volatility with two measures of employment turnover, the worker reallocation rate and the separation rate. The worker reallocation rate is a more comprehensive measure of employment turnover because it accounts for both incoming and outgoing employees. For these measures, we follow the definitions of Abowd et al. (2009) and Abowd and Vilhuber (2011). The worker reallocation rate ($WRR$) for establishment $i$ in year $t$ is defined as:

$$WRR_{it} = \frac{A_{it} + S_{it}}{0.5 \times (E_{it} + E_{it-1})},$$

where $A_{it}$ is the number of accessions in year $t$ at establishment $i$, $S_{it}$ is the number of separations from establishment $i$ in year $t$, and $E_{it}$ is previously defined.

The second measure of employment turnover, the separation rate, only accounts for employees separating from an establishment or firm. The establishment-level separation rate ($SR$) for establishment $i$ in year $t$ is calculated as follows:

$$SR_{it} = \frac{S_{it}}{0.5 \times (E_{it} + E_{it-1})}.$$

Similar to the employment growth rates, we take an employment-weighted average of establishment $WRR_{it}$ and $SR_{it}$ to calculate firm-level $WRR_{ft}$ and $SR_{ft}$ for firm $f$ in year $t$.

Both employment volatility measures are bounded below by zero, with lower numbers indicating lower levels of employment volatility. However, both measures are unbounded above and low employment in the denominator can lead to very large values for these measures. Therefore, we trim the top 1% of observations based on the $WRR_{ft}$ or $SR_{ft}$ when conducting those analyses. We only present and discuss the results for firm
because the results for $WRR_{ft}$ yield extremely similar patterns to those for $SR_{ft}$.

For the third phase of the project, we condition the analysis of job creation on a measure of job stability to determine what types of firms create stable jobs. We rely on two definitions of job stability to determine if each individual job is stable. The first definition of job stability, a current measure, uses the tenure of each worker to determine if each job in the sample is stable. The second definition, which is forward-looking, uses worker retention to define a stable job.

We follow the work of Abowd and Vilhuber (2011) and Hyatt and Spletzer (2016) for the following definitions. Stable-worker tenure ($SWT$) of length $k$ for worker $j$ at firm $f$ at time $t$ is defined as:

$$SWT^k_{jft} = \begin{cases} 1, & \text{if } T_{jft} \geq k \text{ and } e_{jft} = 1 \text{ for all } t = t, \ldots, t + k \\ 0, & \text{otherwise} \end{cases}, \quad (1.1)$$

where $T_{jft}$ is the worker’s tenure at firm $f$ in year $t$ and $e_{jft}$ is worker $j$’s employment status at firm $f$ in December of year $t$. We calculate tenure at the firm level to account for the possibility of workers moving between establishments in order to climb the corporate ladder within a given firm.$^5$ By construction, using the worker’s tenure to define a stable job does not allow any firm less than $k$ years in age to have any workers with a stable job.

The second definition of job stability uses the concept of retention to determine whether each job in the sample is stable. A worker $j$ at firm $f$ has stable-worker retention ($SWR$) of length $k$ at time $t$ if the worker is continuously employed at firm $f$ between year $t$ and $t + k$.

$$SWR^k_{jft} = \begin{cases} 1, & \text{if } e_{jft+g} = 1 \text{ for } g = 0..k \\ 0, & \text{otherwise} \end{cases}, \quad (1.2)$$

where $e$ is previously defined. As with $SWT^k_{jft}$, we calculate retention at the firm level to

$^5$Calculating tenure at the establishment level does not significantly alter the results.
account for employees switching establishments to move up within a given firm.\(^6\)

We then sum these measures across employees at each firm to get the number of stable workers at each firm. Stable-firm tenure \((SFT)\) of length \(k\) for firm \(f\) in year \(t\) is defined as:

\[
SFT^k_{ft} = \sum_{j=1}^{E_{ft}} SWT^k_{jft},
\] (1.3)

and stable-firm retention \((SFR)\) is defined similarly:

\[
SFR^k_{ft} = \sum_{j=1}^{E_{ft}} SWR^k_{jft}.\] (1.4)

These measures are counts of the number of workers with stable jobs at each firm \(f\) in year \(t\).

In order to determine what types of firms create stable jobs, we also calculate stable employment growth rates. We calculate them twice for each firm, once using worker tenure and again using worker retention. Stable employment growth rates are augmented from the employment growth rate used in the job creation analysis (equation 1) to account for firm size as well as the number of stable jobs created. It captures how many stable jobs the firm creates relative to that firm’s size. The stable employment growth rate using worker tenure of length \(k\) \((SGT)\) for firm \(f\) in year \(t\) is calculated as follows:

\[
SGT^k_{ft} = \frac{SFT^k_{ft} - SFT^k_{ft-1}}{0.5 \times (E_{ft} + E_{ft-1})},
\] (1.5)

where the numerator is the number of stable jobs created (or destroyed) at firm \(f\) in year \(t\) and \(E_{ft}\) is employment at firm \(f\) in December of year \(t\). To account for the high number of young firms that exit the market, all destroyed firms have \(SFT^k_{ft} = -2\) for the year of destruction, regardless of whether the firm created any stable jobs. However, by construction, \(SFT^k_{ft}\) is undefined for all firms less than \(k\) years of age (unless the firm was

\(^6\)Calculating tenure at the establishment level does not significantly alter the results.
destroyed as previously described). Therefore, we also calculate the stable employment growth rate using worker retention to define a stable job.

The stable employment growth rate using worker retention of length \(k\) (\(SGR\)) for firm \(f\) in year \(t\) is calculated as follows:

\[
SGR_{ft}^k = \frac{SFR_{ft} - SFR_{ft-1}}{0.5 \times (E_{ft} + E_{ft-1})},
\]  

(1.6)

where \(SFR_{ft}^k\) and \(E_{ft}\) are previously defined. Due to the fact that the retention measure is forward looking, we are unable to calculate \(k\)-year retention rates for the last \(k\) years in the sample. In line with how \(SFR_{ft}^k\) is defined for destroyed firms, \(SGR_{ft}^k\) is undefined in year \(t - k + 1\) through year \(t\) and equal to -2 in year \(t-k\) for firms destroyed in year \(t\).

Both \(SGR_{ft}^k\) and \(SGT_{ft}^k\) are bounded below by -2 and bounded above by 2, with higher numbers indicating a higher growth rate of stable jobs. For our main analysis, we use \(k = 2\). For tenure, this means that a worker must have current firm-level tenure of at least 2 years and still be employed at the firm in December to have a stable job. For retention, a worker must continue to be employed at the same firm for the following two years to have a stable job. As a robustness check, we also use \(k = 1\) and \(k = 3\) and do not find any qualitative change in the results.

1.4 Data

The data comes from the Relação Anual de Informações Sociais (hereafter, RAIS) collected annually by the Brazilian Ministry or Labor (MTE - Ministerio do Trabalho e Emprego). The data is collected for all formal establishments in Brazil as part of a program where qualified workers receive a bonus at the end of the year equal to one month’s salary (or a prorated amount if the worker worked less than 12 months). This 13th month salary is paid by the employer but facilitated by MTE. Hence, both employers and employees
have great interest in ensuring accurate information is reported to MTE.\footnote{Workers will ensure wages are not under-reported and firms will ensure wages are not over-reported.} For this project, we use RAIS for years 2004 through 2013. RAIS has unique identifiers for workers, establishments, and parent firms, resulting in a linked employer-employee data set that allows researchers to track firms, establishments, and workers across time. An establishment represents a single location of a business while the parent firm represents all establishments under common ownership. The ability to track both establishments and their parent firms over time is important for accurately measuring employment growth, firm entry, and firm exit (HJM).

The unit of observation in RAIS is the individual worker, each with a unique personal identification number. Each worker-year record in RAIS has an establishment identification number associated with it and the first eight digits of the establishment identification number identify the parent firm. The establishment and firm identification numbers are used to construct establishment- and firm-level characteristics for each observation. In order to compare the job creation results for Brazil with the literature, we restrict our analysis to private, for-profit firms. Further, we drop observations that are unusable for the analysis: those with zero wages, those without a personal or establishment identification number, and those that are not subject to labor regulations.\footnote{0.24\% of observations are dropped due to no personal or establishment identification number and 1.9\% of observations are dropped because they are not subject to labor regulations.}

For the initial job creation analysis, we only keep workers employed in December of each year. This is consistent with HJM’s point-in-time measure of employment. In the appendix, we also consider firms that existed for less than one year. These are firms that have records in our data, but had zero workers employed in December. We do include these short-lived firms in the employment turnover and job stability analysis to capture all of the volatility of job creation and destruction.

The RAIS data does not provide information on establishment age or firm age, so we use the hire date of each worker and the panel structure of the data to construct age
variables. To calculate establishment age, we begin with the year the establishment first appeared in the panel. We calculate establishment age for the first year as the difference in the first year and the earliest hire year of any employee working at the establishment in that year. For example, if the establishment first appears in the panel in the year 2004, establishment age is calculated as the difference in the year (2004) and the earliest hire year of any employee working at the establishment in 2004. For each additional year an establishment identification number appears in the data, we allow the establishment to age naturally. To calculate firm age, we take the maximum age of all establishments controlled by the firm in the first year and then allow the firm to age naturally by one year for each additional year the firm appears in the panel. For example, suppose a firm controls three establishments in year 2004, its first year in the panel, with establishment ages of 5, 10, and 2. Then, firm age for 2004 equals 10, the maximum age of the three establishment ages. For each additional year the firm appears in the data, we allow the firm to age naturally.

However, these constructed measures of establishment age and firm age variables may be measured with error. Establishment age could underestimate true establishment age if all the original workers at the establishment are no longer employed in 2004. It is also possible that our establishment age and firm age variables overestimate true establishment and firm age if the hire date variable is measured with error. For example, establishment identification numbers first appearing in the panel in the year 2005 or later should be new establishments. However, we observe several establishments first entering the panel in 2005 or later with an earliest employee hire year prior to 2005. Therefore, we perform a consistency check on the constructed age variables to determine how significant an issue measurement error is. We calculate the observed establishment age for establishments first appearing in the panel in 2005 or later as the difference in the current year and the first year (true establishment age). Then, we compare this to the establishment age previously described, which we calculate using the minimum hire year of all employes (hire date establishment age).
We find that our method for calculating establishment and firm age based on employee hire dates overestimates observed establishment age for approximately 9% of establishments and overestimates observed firm age for approximately 7.2% of firms. Using firm age classes, rather than actual firm age, helps minimize the issue. The firm age class variable overestimates observed firm age class for approximately 5.3% of firms. We repeat the age consistency checks for establishment that first appear in the data in 2006 or later. In theory, these are more likely to be truly new establishments because they do not have data for 2004 or 2005. We find very similar, but slightly smaller results in comparison to those using 2005 and later. The results for the age consistency checks are shown in Table 1.2 and 1.3 in the appendix.

Ultimately, we have 260,479,528 worker-year observations with non-zero wages in December working for private, for-profit establishments for the ten-year panel. We aggregate the worker-level data up to the establishment level, keeping one observation per establishment per year, a total of 21,562,744 establishment-year observations. Then, we aggregate the establishment-level data up to the firm level, keeping one observation per firm per year, a total of 18,998,490 observations.

The summary statistics for the establishment- and firm-level data are presented in Table 1.1. Each establishment-year is categorized as new, continuing, or destroyed. An establishment is considered new if the establishment identification number first appears in the data in 2005 or later, or if the establishment identification number first appears in the data in 2004 and the hire date for all employees equals 2004. An establishment is considered continuing for each additional year the establishment identification appears in the data or if the establishment first appears in the data in 2004 and the hire date for at least one employee is less than 2004. An establishment is considered destroyed in the year after the establishment identification number last appears in the data. For example, suppose an establishment identification number first appears in the data in 2006 and continues to appear in the data in 2007 and 2008. The establishment is new in 2006,
continuing in 2007 and 2008, and destroyed in 2009. Table 1.1 shows that approximately 14% of all establishments are new, 74% are continuing, and 12% exit the market. Each firm-year observation is also categorized as new, continuing, or destroyed in a similar manner as establishments. The proportion of new, continuing, and destroyed firms are similar to those for establishments.

The summary statistics in Table 1.1 also reveal that the average establishment and
average firm are relatively small (11 to 13 employees) and relatively young (just under 6 years in age). As noted in section 3, the analyses rely on a point in time measure of employment. We use December of each year as our point in time to measure employment at the worker-, establishment-, and firm-level. Formal definitions of our employment measures are included in the appendix.

Figure 1.1 shows the share of employment and stable jobs by industry using both tenure and retention to measure job stability. The first and second bar for each industry show the share of stable jobs in that industry relative to the total number of stable jobs across all industries using tenure and retention, respectively. For example, over 30% of all stable jobs are in the manufacturing industry, nearly 27% of all stable jobs are in the retail and wholesale industry, and only 1% of all stable jobs are in real estate. The share of stable jobs dramatically varies by industry, but is nearly identical under the two measures of stability. The third bar for each industry shows the share of overall employment in each industry. Comparing the first two bars for each industry with the third bar indicates whether each industry has relatively more or fewer stable jobs than its share of overall employment. For example, manufacturing has relatively more stable jobs and retail has relatively fewer stable jobs than their share of employment.

Figure 1.2 shows the percent of jobs within each industry that are stable, by both the tenure and retention definitions. The figure shows that mining, financial services, and utilities have the highest percentage of stable jobs, whereas construction and real estate have the lowest percentage.

1.5 Results

1.5.1 Job Creation and Destruction

Figure 1.3 summarizes the patterns for employment, job creation, and job destruction for Brazil for the years 2005-2013 by three size classes (using base-year size)
Figure 1.1: Shares of Stable Jobs by Industry: Brazil, 2005-2013

Notes: RAIS data, 2005 - 2013. The first bar for each industry shows the share of stable jobs in that industry relative to the total number of stable jobs in all industries using worker tenure. The second bar shows the similar statistic using worker retention to measure stability. The third bar shows the share of employment in that industry relative to overall employment. The industries are sorted by employment shares.

The figure shows the share of employment, job creation, and job destruction for small firms (less than 50 employees) in the left panel, medium firms (between 50 and 500 employees) in the middle, and large firms (500 employees and above) in the right panel by firm births, young firms (less than ten years old), and mature firms (10 years and above). Figure 1.3 shows that small-young firms (the middle three columns in the left panel) account for the highest share of employment, job creation, and job destruction in Brazil. Small-firm births create a higher percentage of jobs (16%) relative to

9HJM used two size categories (Figure 1 in HJM). Brazil has a much higher share of firms with less than 500 employees than the US, so the addition of a third category provides more insight into the Brazilian labor market. The comparable figure for Brazil with just two size classes is shown as Figure 1.17 in the appendix.
Notes: RAIS data, 2005 - 2013. The first bar for each industry shows the share of stable jobs within that industry using worker tenure. The second bar shows the similar statistic using worker retention to measure stability. The industries are sorted by percent stable (Tenure).

their share of employment (2%) and small-mature firms create a lower percentage of jobs (9%) relative to their share of employment (16%). By construction, firm births can only create jobs and cannot destroy jobs. We also see that most firm births and young firms are also small firms. In all size categories, mature firms have lower job creation than their share of employment, suggesting the important role of young firms in job creation.

Comparing these statistics to the US, the most noticeable difference is where employment, job creation, and destruction are concentrated. For the US, the share of employment, job creation, and job destruction is concentrated in large-mature firms, 45%, 35%, and 40% respectively (HJM). For Brazil, small-young firms account for the highest
Figure 1.3: Shares of Employment, Job Creation, and Destruction by Broad Firm Size and Age Classes: Brazil, 2005-2013

Notes: RAIS data, 2005 - 2013. Shares of employment, job creation, and job destruction are calculated using establishment-level data characterized by three firm base size classes and three firm age classes. Firm births only create jobs and cannot destroy any jobs by definition.

percentages of each category. Criscuolo et al. (2014) show that some OECD countries also have large shares of employment in small firms, such as Spain and Italy. However, young firms play a much larger role in Brazil than in any other country Criscuolo et al. (2014) study. Firms less than five years old in Brazil account for around 65% of all small firms; Spain has the next highest share at 45% (Criscuolo et al., 2014).

Figure 1.4 shows the relationship between employment growth rates and firm size. It plots the estimated coefficients for both one-way and two-way models of employment growth rates by firm size, using both base size and average size, with and without age controls. Standard errors are extremely small in all our analyses because the data has around 20 million observations and therefore are not shown on the figures. The plotted estimates for the one-way model using firm base size (diamond markers) show an inverse relationship between firm size and employment growth. The average employment growth rate for the smallest firms (base size 1 to 4) is about 30 percentage points higher than that
Figure 1.4: Employment Growth Rate and Firm Size

![Graph showing employment growth rate and firm size]

Notes: RAIS data, 2005 - 2013. The figure shows estimates for one-way models of employment growth by firm size class and estimates for two-way models of employment growth by firm size class controlling for firm age class (using both base size and average size). A higher value indicates that a particular firm size class has a higher firm growth rate relative to other firm size classes.

for the largest firms (base size of 500 or more). The growth rate monotonically declines with firm base size class. The plotted estimates for the one-way model using firm average size (square markers) show a mildly decreasing relationship between firm size and employment growth. The employment growth rate of the smallest size class (average size 1 to 4) is approximately 12 percentage points higher on average than that for the largest firms (average size greater than or equal to 500). Including controls for firm age changes the relationship between employment growth and firm size. The plotted curves of the two-way models show an increasing relationship between employment growth and both size measures (the base size curve has a slight decrease initially). Once age controls are included, small firms no longer have the highest employment growth rates.

Next, we look at the relationship between firm size and firm exit. Figure 1.5 plots the estimated coefficients for the one-way and two-way models of job destruction due to
Figure 1.5: Firm Exit by Firm Size

Notes: RAIS data, 2005 - 2013. The figure shows estimates for one-way models of firm exit by firm size class and for two-way models of firm exit by firm size class controlling for firm age class. A higher value indicates that a particular firm size class has a higher firm exit rate relative to other firm size classes.

Firm exit by firm size, without and with age controls respectively. As HJM note, “Job destruction from firm exit is directly interpreted as an employment-weighted firm exit rate” (p. 356). Firm exit rates decrease monotonically with firm base size and firm average size, with and without age controls. Small firms are more likely to shut down and exit, regardless of whether age controls are included. Relative to the largest firm size class, the smallest firms have average exit rates approximately 15 percentage points higher using base size and around 25 percentage points higher using average size, with and without age controls. To further analyze the relative importance of firm age and size, we next estimate the relationship between firm growth rates and firm age, with and without controls for firm size.

Figure 1.6 plots the estimated coefficients for one-way and two-way models of
employment growth rates by firm age, without and with firm size controls respectively. First, we look at coefficients for the one-way model of employment growth rates by firm age (diamond markers). Without firm size controls, the youngest firms (age one to two) have the highest employment growth rates. The relationship is initially decreasing, but eventually stabilizes. This result differs from HJM, who found an increasing relationship (Figure 4a in their paper). However, the difference is likely explained by the different size-age distributions of firms between the two countries. As previously shown in Figure 1.3, Brazil has a very large concentration of small-young firms, and so, even when not controlling for firm size, most of the young firms are also small. The plotted coefficients for the two-way models, which control for firm age and either firm base size (triangle markers)

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Notes: RAIS data, 2005 - 2013. The figure shows estimates for one-way models of employment growth by firm age class and estimates for two-way models of employment growth by firm age class controlling for firm size class (using both base size and average size). A higher value indicates that a particular firm age class has a higher firm growth rate relative to other firm age classes. Results for new firms are not displayed.

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10 The estimated coefficients for firm start-ups are not displayed in the figure since the coefficients are equal to exactly two (by definition of the growth measure).
Figure 1.7: Firm Exit by Firm Age

Notes: RAIS data, 2005 - 2013. The figure shows estimates for one-way models of firm exit by firm age class and for two-way models of firm exit by firm age class controlling for firm size class (using both base size and average size). A higher value indicates that a particular firm age class has a higher firm exit rate relative to other firm age classes. New firms are excluded from the figure because they cannot destroy any jobs by construction.

or firm average size (square markers), indicate the youngest firms still have the highest employment growth rates and the relationship between employment growth and firm age is mildly decreasing. We also perform this analysis on the set of continuing firms only but do not present those results to conserve space. Those results show a similar pattern, but that young surviving firms have even higher growth rates than the sample of all firms.

Figure 1.7 plots the estimated coefficients for one-way and two-way models of job destruction from firm exit by firm age. The coefficients for both one-way and two-way models of firm exit by firm age show similar relationships. Without firm size controls, firm exit rates decrease monotonically with firm age. With firm size controls, firm exit rates initially decrease with firm age and eventually stabilize (with a slight increase for the oldest firms using firm average size controls). Together, Figure 1.6 and Figure 1.7 show that
young firms have higher employment growth rates than more mature firms and that young firms are more likely to shut down and exit the market than more mature firms.\footnote{In the appendix, Figure S4 shows these results by broad sectors and shows that results are similar across sectors.}

These patterns for job creation and destruction by firm age for Brazil are similar to HJM’s results for the US and Criscuolo et al.’s (2014) results averaging across Brazil and 17 OECD countries. That is, firm age is a more important determinant of job creation and destruction than is firm size. While Criscuolo et al. (2014) examine the average relationship across 18 countries, we show the importance of firm age for job creation is also true of just Brazil. The results also highlight the importance of the “up-or-out pattern”, summarized by HJM, “Each wave of firm start-ups create a substantial number of new jobs. In the first years following entry, many start-ups fail, but the surviving young businesses grow very fast” (p. 358). This pattern is potentially more relevant for Brazil, due to the greater presence of young firms in Brazil relative to the other countries studied by Criscuolo et al. (2014).

1.5.2 Young Firms and Employment Volatility

Thus far, the results highlight the significant role that firm start-ups and young firms play in the Brazilian economy. However, young firms may not provide very stable jobs, partly due to the higher exit rates shown in Figure 1.7, but also due to new firms searching for the right workers. To explore the volatility of jobs in Brazil, we analyze worker reallocation rates ($WRR$) by firm size and firm age. A higher $WRR$ indicates higher levels of employment volatility, which is costly to both workers and firms.

We continue to follow HJM’s methodology and present the results in figures. Figure 1.8 shows coefficients from the analysis of $WRR$ by firm size, with and without age controls. The results for the one-way models show that $WRR$ is relatively flat for both firm size measures for firms with less than 250 employees. The relationship between $WRR$ and firm size begins to decrease for firms with at least 250 employees. The estimates for two-way models with firm age controls show volatility increasing with firm size for firms.
between 5 and 250 employees, but it eventually becomes a decreasing relationship for the largest firms. The results are extremely similar regardless of which size measure is used.

With age controls, firms size 100 - 249 have the largest worker reallocation rates (1.60 and 1.62 on average), while firms 5-9 or 1-4 have the smallest (1.23 and 1.06 on average), using base size and average size respectively. This translates to a 30% or 52.8% higher worker reallocation rate for the larger firms using base and average size, respectively. Using a back-of-the-envelope calculation, we see that the average firm size 100 - 249 would have approximately 100 fewer workers reallocate if their worker reallocation rate was equal to $WRR$ for the smallest firms. Therefore, with firm age controls, we see very economically significant differences between worker reallocation rates for small and large firms.

The analysis of $WRR$ by firm age is of more interest for exploring the “up-or-out
Figure 1.9: Worker Reallocation Rate by Firm Age

Notes: RAIS data, 2005 - 2013. The figure shows estimates for one-way models of worker reallocation rates by firm age class and estimates for two-way models of worker reallocation rates by firm age class controlling for firm size class (using both base size and average size). A higher value indicates that a particular firm age class has a higher worker reallocation rate relative to other firm age classes.

dynamic* of firm start-ups and young firms. Figure 1.9 shows the estimated coefficients for one-way and two-way models of $WRR$ by firm age, without and with firm size controls respectively. The estimates for the one-way models indicate that $WRR$ is decreasing with firm age. The estimates for the two-way models with firm size controls show that reallocation rates continue to decrease with firm age. The figure indicates that employment volatility is relatively high for firm start-ups and young firms in Brazil. With firm size controls, firm start-ups have average $WRR$ of 3.22 and 3.24 using base and average size respectively. The oldest firms (age 16+) have average $WRR$ of 1.08 and 1.05 using base and average size respectively. Using a back-of-the-envelope calculation, if the oldest firms had $WRR$ equal to the $WRR$ for firm start-ups, this would translate to approximately 150 more workers reallocating.
We also conducted the analysis for worker reallocation rates by firm size and firm age for continuing firms only. However, the results for continuing firms only are nearly identical to the results for all firms. Therefore, the results for continuing firms only are presented in the appendix (Figure S5). Last, to ensure the relatively high levels of employment volatility are not driven by a high number of accessions, we also analyze firm separation rates ($SR$), an alternative measure of employment volatility, by firm size and firm age. We continue to find very similar results and therefore do not include those results. Analyzing employment volatility by firm size and firm age helps motivate the need to condition the job creation analysis on a measure of job stability.

### 1.5.3 Job Stability and Job Creation in Brazil

The analysis thus far indicates that firm start-ups and young firms have higher employment growth rates relative to more mature firms in Brazil. Firm start-ups and young firms also have higher levels of firm exit and employment volatility. Therefore, we now condition the job creation analysis on job stability to determine what types of firms create stable jobs in Brazil. Figure 1.10 summarizes the share of employment and the share of stable jobs by broad firm size and firm age classes in Brazil. The figure shows the share of employment, share of stable jobs using worker tenure, and the share of stable jobs using worker retention for small firms (less than 50 employees) in the left panel, medium firms (between 50 and 500 employees) in the middle, and large firms (500 employees and above) in the right panel by firm births, young firms (less than ten years old), and mature firms (10 years and older). Figure 1.10 shows that small-young firms account for over 28% of employment, 23% of stable jobs using tenure to define stability, and 28% of stable jobs using retention to define stability. While Figure 1.3 shows that employment, job creation, and job destruction are concentrated in small-young firms, Figure 10 shows that the share of stable jobs are concentrated in both small-young firms and large-mature firms. Large-mature firms have the highest share of stable jobs using worker tenure (29%) and small-young firms have the highest share of stable jobs using worker retention (28%).
Figure 1.10: Shares of Employment and Stable Jobs by Broad Firm Size and Age Classes: Brazil, 2005-2013

Notes: RAIS data, 2005 - 2013. The figure shows the share of employment, the share of stable jobs using tenure to measure stability, and the share stable jobs using retention to measure stability by three firm base size classes and three firm age classes. Firm births are excluded from having any stable jobs using tenure to measure stability by construction.

Large-mature firms also have a higher share of stable jobs relative to their share of employment.

Figure 1.11 plots the estimated coefficients for one-way and two-way models of stable employment growth rates using tenure to define stability ($SGT$) by firm size. The estimates for one-way models of $SGT$ show that stable growth rates monotonically decrease with firm size without firm age controls (diamond and square markers). Without age controls, the smallest firms have $SGT$ approximately 8 and 6 percentage points higher than the largest firms using base and average size, respectively. The coefficients from the two-way models show the relationship between stable growth rates using tenure and firm size becomes relatively constant or mildly increasing when firm age controls are included (triangle and X markers). When age controls are included, the largest firms have $SGT$ approximately 2 percentage points higher than firms size 5-9.
Figure 1.11: Stable Employment Growth by Firm Size (Tenure)

Notes: RAIS data, 2005 - 2013. The figure shows estimates for one-way models of stable employment growth (tenure) by firm size class and estimates for two-way models of stable employment growth (tenure) by firm size class controlling for firm age class (using both base size and average size). A higher value indicates that a particular firm size class has a higher stable growth rate relative to other firm size classes.

Figure 1.12 also plots the coefficients for one-way and two-way models for stable employment growth rates by firm size, but uses worker retention to measure job stability. The one-way models show that stable employment growth rates using retention (SGR) initially decrease with firm size without age controls for firms smaller than 100 employees. But, the two-way models show that the relationship becomes strictly positive when age controls are included. The largest firms have SGR approximately 9 and 17 percentage points higher than the smallest firms. Across Figures 1.11 and 1.12, the relationship between stable growth rates and firm size changes when age controls are included using both tenure and retention to measure job stability. With age controls, large firms have relatively higher stable employment growth rates than small firms. This relationship is more pronounced using retention rather than tenure.

To further investigate the “up-or-out” dynamic of young firms and firm start-ups,
we also analyze stable employment growth rates by firm age. Figures 1.13 and 1.14 show the results for one-way and two-way models of stable employment growth using tenure ($SGT$) and retention ($SGR$) respectively, by firm age. Figure 1.13 shows that $SGT$ decreases with firm age for both the one-way and two-way models. The results are very robust to including firm size controls. For all models, firms age 3-4 have $SGT$ approximately 10 percentage points higher than the oldest firms (age 16+). Figure 1.13 excludes the estimates for firm ages zero to two because only firms at least two years in age can create stable jobs by the tenure definition of a stable job.

Figure 1.14 shows coefficients for the one-way and two-way models for stable employment growth rates using retention to measure stability ($SGR$) and firm age. $SGR$ initially sharply decrease with firm age, but quickly stabilize, regardless of firm size controls. Firm start-ups, or new firms, create the most stable jobs in Brazil relative to all
Notes: RAIS data, 2005 - 2013. The figure shows estimates from one-way models of stable employment growth (tenure) by firm age class and estimates for two-way models of stable employment growth (tenure) by firm age class controlling for firm size class (using both base size and average size). A higher value indicates that a particular firm age class has a higher stable growth rate relative to other firm age classes.

other age classes. The “up-or-out” dynamic present in the job creation and destruction results in section 5.1 is also prevalent in the results for stable employment growth rates. Conditional on survival, young firms create relatively more stable jobs in Brazil. The analysis continues to support the idea that firm age is an important determinant of employment dynamics in Brazil.

The analysis of stable employment growth rates shows that both firm size and firm age are key determinants of stable employment growth in Brazil. The results for the one-way and two-way models indicate that larger firms and younger firms create relatively more stable jobs in Brazil, seen through higher estimated stable employment growth rates.
Figure 1.14: Stable Employment Growth by Firm Age (Retention)

Notes: RAIS data, 2005 - 2013. The figure shows estimates from one-way models of stable employment growth (retention) by firm age class and estimates for two-way models of stable employment growth (retention) by firm age class controlling for firm size class (using both base size and average size). A higher value indicates that a particular firm age class has a higher stable growth rate relative to other firm age classes.

1.6 Conclusion

This project uses the RAIS (Relação Anual de Informações Sociais) data from Brazil to first analyze job creation and job destruction patterns by firm size and firm age. The project then examines employment volatility by firm age and firm size. Last, we condition the job creation analysis on two measures of job stability to determine what types of firms create stable jobs in Brazil.

The first glimpse at the Brazil data shows that employment, job creation, and job destruction are most concentrated in small-young firms. Our results also show firm age is a more important determinant of employment growth than firm size. Including firm age controls significantly alters the relationship between employment growth and firm size, but including firm size controls does not change the relationship between employment growth
and firm age. The results indicate that firm start-ups and young firms create a disproportionately high number of jobs in Brazil. However, young firms also experience much higher exit rates relative to more mature firms. The “up-or-out” dynamic of young firms in the US described by HJM is also present in Brazil. The fact that young firms exit the market at a disproportionately high rates suggests that young firms are inherently volatile. Therefore, we analyze a measure of employment volatility, the worker reallocation rate, by firm size and firm age. The results indicate that younger firms have higher levels of volatility, even after conditioning on survival.

To account for young firms’ high levels of employment volatility, we condition the employment growth analysis on two measures of job stability, one using worker tenure, a current measure, and one using worker retention, a future measure, to define a stable job. Using worker tenure, we define a job as stable in year $t$ if the worker has been employed at the firm for at least two years. We use a second measure of stability, retention, and define a job as stable in year $t$ if the worker is continuously employed at the same firm for two additional years. The analysis of stable growth rates indicates that both firm size and firm age are important determinants of stable employment growth in Brazil. Not only are young firms creating a relatively higher number of jobs in Brazil, but young firms also have relatively higher stable employment growth rates. Large firms also have relatively higher stable employment growth rates. These results are consistent under both measures of stability.

Overall, using data from the RAIS for 2004 - 2013, our analysis confirms the important role firm age plays when analyzing job creation and destruction. Young firms and firm start-ups contribute to job creation and job destruction at a disproportionately high rate. Further, we find that both firm size and firm age are important determinants of stable employment growth in Brazil. The results show why it is important for researchers and policymakers to consider firm size, firm age, and job stability when analyzing employment growth. Policymakers simply cannot afford to focus on only firm size or firm
age when creating policies to promote employment growth, particularly when promoting the creation of stable jobs. Policies promoting dominantly small firms ignore firm age, a crucial determinant of employment growth and stable employment growth. But, policies promoting primarily new firms ignore the volatility inherent to new and young firms.

1.7 Appendix

1.7.1 Worker, Establishment, and Firm Concepts and Definitions

Worker-Level Concepts. We calculate all worker-level concept for the years \( t = 2004, \ldots, 2013 \).

**December Employment** \((e)\): A worker \( j \) employed at establishment \( i \) in December of year \( t \).

\[
e_{jit} = \begin{cases} 
1, & \text{if } j \text{ has positive earnings at establishment } i \text{ in December of year } t \\
0, & \text{otherwise.}
\end{cases}
\]

Replacing subscript \( i \) with \( f \) gives a worker \( j \)'s employment at firm \( f \) in December of year \( t \).

**Accession** \((a)\): A worker \( j \) was hired or recalled for employment at establishment \( i \) during year \( t \).

\[
a_{jit} = \begin{cases} 
1, & \text{if } hire\_year_{jit} = t \\
0, & \text{otherwise.}
\end{cases}
\]

where \( hire\_year_{jit} \) is the year \( t \) worker \( j \) was hired at establishment \( i \), which is provided in the data.

**Separation** \((s)\): A worker \( j \) separated from establishment \( i \) during year \( t \).

\[
s_{jit} = \begin{cases} 
1, & \text{if } sep\_year_{jit} = t \\
0, & \text{otherwise.}
\end{cases}
\]

where \( sep\_year_{jit} \) is the year \( t \) worker \( j \) separated from establishment \( i \), which is provided
in the data.

Tenure (T): A worker \( j \) has tenure, measured in years, at establishment \( i \) in December of year \( t \).

\[
T_{jit} = \frac{\text{time\_of\_employment}_{jit}}{12}
\]

where \( \text{time\_of\_employment}_{jit} \), which is given in the data, is the amount of time (measured in months) that worker \( j \) has been employed at establishment \( i \) in December of year \( t \).

We also calculate tenure for worker \( j \) at firm \( f \) in December of year \( t \). We first define the worker’s tenure at establishment \( i \) (owned by firm \( f \)) for the first year the worker-firm pair appears in the data, \( first\_year\_tenure_{jif} \). Then, for each additional year \( n \) worker \( j \) works at any establishment owned by firm \( f \), we calculate worker \( j \)'s tenure at firm \( f \) as follows:

\[
T_{jfn} = first\_year\_tenure_{jif} + (n - t) \text{ where } n > t \text{ and } e_{jft} = 1 \text{ for all } t = t, \ldots, t + n.
\]

Retention (retention): A worker \( j \) has retention of \( k \) years at establishment \( i \) in December of year \( t \).

\[
k^k_{jit} = \begin{cases} 
1, & \text{if } e_{jir} = 1 \text{ for all } \tau = t, \ldots, t + k \\
0, & \text{otherwise.}
\end{cases}
\]

Replacing the \( i \) subscript with \( f \) gives worker \( j \)'s \( k \)-year retention at firm \( f \) at time \( t \).

Establishment-Level Concepts. We calculate the first 4 establishment-level concepts for the years \( t = 2004, \ldots, 2013 \).

Employment (E): Employment at establishment \( i \) in December of year \( t \).

\[
E_{it} = \sum_j e_{jit}
\]
Accessions ($A$): accessions at establishment $i$ during year $t$.

$$A_{it} = \sum_j a_{jit}$$

Separations ($S$): separations from establishment $i$ during year $t$.

$$S_{it} = \sum_j s_{jit}$$

Establishment Age ($estab\_age$): Establishment $i$’s age (measured in years) in year $t$.

$$estab\_age_{it} = t - \min(hire\_year_{jit})$$ for all $j$ employed at $i$ in year $t$ if $t = first\_year_i$

where $first\_year_i$ is the first year an establishment $i$ appears in the data.

For each additional year $n$ the establishment appears in the data, we allow the establishment to age naturally as follows:

$$estab\_age_{in} = estab\_age_{it} + (n - t)$$

where $t = first\_year_i$ and $n > t$.

We calculate the remaining establishment-level concept for the years $t = 2005, ..., 2013$.

Job Destruction from Establishment Exit ($JD\_Exit$): Job destruction from establishment $i$ exit in year $t$.

$$JD\_Exit_{it} = \max(-G_{it}, 0) * I(-G_{it} = 2)$$

New Establishment ($estab\_new$): An indicator variable to identify whether an establishment $i$ is considered new in year $t$.

$$estab\_new_{it} = \begin{cases} 1, & first\_year_i = t \text{ for } t > 2004 \\ 0, & \text{otherwise.} \end{cases}$$
Continuing Establishment (estab_cont): An indicator variable to identify whether establishment $i$ is continuing in year $t$.

$$estab\_cont_{it} = \begin{cases} 1, & t > first\_year_{i} \text{ and } E_{it} > 0 \text{ for } t > 2004 \\ 0, & \text{otherwise}. \end{cases}$$

Destroyed Establishment (estab_dest): An indicator variable to identify whether establishment $i$ is destroyed in year $t$.

$$estab\_dest_{it} = \begin{cases} 1, & E_{it-1} > 0 \text{ and } E_{it} = 0 \text{ for } t > 2004 \\ 0, & \text{otherwise}. \end{cases}$$

Base Size (base_size): Base size for establishment $i$ in year $t$ (for $t > 2004$).

$$base\_size_{it} = \begin{cases} E_{it}, & \text{if } estab\_new_{it} = 1 \\ E_{it-1}, & \text{otherwise}. \end{cases}$$

Average Size (average_size): Average size for establishment $i$ in year $t$ (for $t > 2004$).

$$average\_size_{it} = \frac{E_{it} + E_{it-1}}{2}.$$ 

Firm-Level Concepts. We calculate the first 3 firm-level concepts for the years $t = 2004, ..., 2013$.

Employment ($E$) Employment at firm $f$ in December of year $t$.

$$E_{ft} = \sum_{i} E_{it}$$
**Firm Age (firm\_age):** Firm f’s age (measured in years) in year t.

\[ \text{firm\_age}_{ft} = \text{max(\text{estab\_age}_i)} \text{ for all } i \text{ owned by } f \text{ in } t \text{ if } \text{first\_year}_f = t, \]

where first\_year\_f is the first year the firm appears in the data.

For each additional year n the firm appears in the data we allow the firm to age naturally as follows:

\[ \text{firm\_age}_{ft+n} = \text{firm\_age}_{ft} + (n - t) \text{ where } t = \text{first\_year}_f \text{ and } n > t. \]

**Firm Age Class:** Firm f age class in year t.

\[ \text{firm\_age\_class}_{ft} = \begin{cases} 
1, & \text{if } \text{firm\_age}_{ft} = 0 \\
2, & \text{if } 1 \leq \text{firm\_age}_{ft} \leq 2 \\
3, & \text{if } 3 \leq \text{firm\_age}_{ft} \leq 4 \\
4, & \text{if } 5 \leq \text{firm\_age}_{ft} \leq 6 \\
5, & \text{if } 7 \leq \text{firm\_age}_{ft} \leq 8 \\
6, & \text{if } 9 \leq \text{firm\_age}_{ft} \leq 10 \\
7, & \text{if } 11 \leq \text{firm\_age}_{ft} \leq 12 \\
8, & \text{if } 13 \leq \text{firm\_age}_{ft} \leq 15 \\
9, & \text{if } \text{firm\_age}_{ft} \geq 16 
\end{cases} \]

We calculate the remaining firm-level concepts for the years \( t = 2005, \ldots, 2013 \).

**Firm Growth Rate (G):** Firm growth rate for firm f in year t.

\[ G_{ft} = \sum_i \frac{\text{estab\_average\_size}_i}{\text{firm\_average\_size}_{ft}} G_{it} \text{ for all } i \text{ under control of } f. \]
Job Destruction from Firm Exit (JD\_Exit): Job destruction from firm $f$ exit in year $t$.

$$JD\_Exit_{ft} = \sum_i \frac{estab\_average\_size_{it}}{firm\_average\_size_{ft}} I(G_{it} = -2) \max(-G_{it}, 0).$$

Worker Reallocation Rate (WRR): Worker reallocation rate for firm $f$ in year $t$.

$$WRR_{ft} = \sum_i \frac{estab\_average\_size_{it}}{firm\_average\_size_{ft}} WRR_{it} \text{ for all } i \text{ under control of } f.$$ 

Separation Rate (SR): Separation rate for firm $f$ in year $t$.

$$SR_{ft} = \sum_i \frac{estab\_average\_size_{it}}{firm\_average\_size_{ft}} SR_{it} \text{ for all } i \text{ under control of } f.$$ 

New Firm (firm\_new): A firm $f$ is considered new in year $t$ if all establishments $i$ under the firm’s control are new (for $t > 2004$).

$$firm\_new_{ft} = \begin{cases} 
1, & \min(estab\_new_{it}) = 1 \text{ for all } i \text{ under control of } f \\
0, & \text{otherwise}.
\end{cases}$$

Continuing Firm (firm\_cont): A firm $f$ is considered continuing in year $t$ if at least one establishment under its control is continuing in year $t$ (for $t < 2004$).

$$firm\_cont_{ft} = \begin{cases} 
1, & \min(estab\_cont_{it}) = 1 \text{ for all } i \text{ under control of } f \\
0, & \text{otherwise}.
\end{cases}$$

Destroyed Firm (firm\_dest): A firm $f$ is considered destroyed in year $t$ if all establishment’s under its control are destroyed (for $t > 2004$).

$$firm\_dest_{ft} = \begin{cases} 
1, & \min(estab\_dest_{it}) = 1 \text{ for all } i \text{ under control of } f \\
0, & \text{otherwise}.
\end{cases}$$
**Base Size (base\_size):** Base size for firm \( f \) in year \( t \) (for \( t > 2004 \)).

\[
\text{base\_size}_{ft} = \begin{cases} 
E_{ft}, & \text{if } \text{firm\_new} = 1 \\
E_{ft-1}, & \text{otherwise.}
\end{cases}
\]

**Average Size (average\_size):** Average size for firm \( f \) in year \( t \) (for all \( t > 2004 \)).

\[
\text{average\_size}_{ft} = \frac{E_{ft} + E_{ft-1}}{2}
\]

**Firm Base Size Class (firm\_base\_class):** Firm \( f \) base size class in year \( t \) (for \( t > 2004 \)).

\[
\text{firm\_base\_class}_{ft} = \begin{cases} 
1, & \text{if } 1 \leq \text{firm\_base\_size}_{ft} \leq 4 \\
2, & \text{if } 5 \leq \text{firm\_base\_size}_{ft} \leq 9 \\
3, & \text{if } 10 \leq \text{firm\_base\_size}_{ft} \leq 19 \\
4, & \text{if } 20 \leq \text{firm\_base\_size}_{ft} \leq 49 \\
5, & \text{if } 50 \leq \text{firm\_base\_size}_{ft} \leq 99 \\
6, & \text{if } 100 \leq \text{firm\_base\_size}_{ft} \leq 249 \\
7, & \text{if } 250 \leq \text{firm\_base\_size}_{ft} \leq 499 \\
8, & \text{if } \text{firm\_base\_size}_{ft} \geq 500
\end{cases}
\]

**Firm Average Size Class (firm\_average\_class):** Firm \( f \) average size class in year \( t \) (for
t > 2004).

\[
\text{firm\_average\_class}_{ft} = \begin{cases} 
1, & \text{if } 1 \leq \text{firm\_average\_size}_{ft} \leq 4 \\
2, & \text{if } 5 \leq \text{firm\_average\_size}_{ft} \leq 9 \\
3, & \text{if } 10 \leq \text{firm\_average\_size}_{ft} \leq 19 \\
4, & \text{if } 20 \leq \text{firm\_average\_size}_{ft} \leq 49 \\
5, & \text{if } 50 \leq \text{firm\_average\_size}_{ft} \leq 99 \\
6, & \text{if } 100 \leq \text{firm\_average\_size}_{ft} \leq 249 \\
7, & \text{if } 250 \leq \text{firm\_average\_size}_{ft} \leq 499 \\
8, & \text{if } \text{firm\_average\_size}_{ft} \geq 500
\end{cases}
\]
1.7.2 Age Consistency Checks

Table 1.2: Establishment and Firm Age Consistency Check, 2005 and Later

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<th>count</th>
<th>mean</th>
<th>median</th>
<th>sd</th>
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<td></td>
</tr>
<tr>
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<td>Percent Overestimated</td>
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</tr>
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<td></td>
<td></td>
</tr>
<tr>
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<td>3.49</td>
<td>1.00</td>
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<td>Percent Overestimated</td>
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<td>Percent Overestimated</td>
<td>(5.63%)</td>
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</tbody>
</table>

Notes: RAIS data, 2005 - 2013. Summary statistics for the establishment-level data in the upper panel and for the firm-level data in the lower panel.
Table 1.3: Establishment and Firm Age Consistency Check, 2006 and Later

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<td>Percent Overestimated</td>
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<table>
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<table>
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<tbody>
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<td>Age Class (True)</td>
<td>7,555,307</td>
<td>2.11</td>
<td>2.00</td>
<td>0.97</td>
</tr>
<tr>
<td>Age Class Difference</td>
<td>360,417</td>
<td>1.98</td>
<td>1.00</td>
<td>1.71</td>
</tr>
<tr>
<td>Percent Overestimated</td>
<td>(5.63%)</td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Notes: RAIS data, 2005 - 2013. Summary statistics for the establishment-level data in the upper panel and for the firm-level data in the lower panel.

1.7.3 Additional Descriptive Statistics

In this section we present more figures describing the RAIS data. First, we present results for the shares of employment, job creation, and destruction, using the same two categories for firm size as HJM. HJM split the sample into two size categories, small firms with up to 500 employees and large firms with over 500 employees. However, Brazil, has many more small firms than the United States. So, for the main analysis we included an additional category for medium sized firms, with employment between 50 and 500. Here, we use the same size categories as HJM. Compared to Figure 1.3 in the text, Figure S1 shows that when combining small and medium sized mature firms into one category, it now has larger shares of employment, job creation and destruction, than do large-mature firms. Both figures show the importance of small-young firms in the Brazilian labor market.
Figure 1.15: Shares of Employment, Job Creation, and Destruction by HJM’s Firm Size and Age Classes: Brazil, 2005-2013

Notes: RAIS data, 2005 - 2013. Shares of employment, job creation, and job destruction are calculated using establishment-level data characterized by two firm base size classes and three firm age classes. Firm births only create jobs and cannot destroy any jobs by definition.

We next show the intensity of young firms by industry in Brazil. Figure S2 shows the share of firms in three different age categories for each industry in Brazil. The first bar for each industry shows the share of new firms. The second bar shows the share of firms between 1 and 5 years old. The third bar shows the share of firms between 6 and 10 years old. Note the bars for each industry do not sum to one as mature firms are excluded from this figure. However, given the prevalence of young firms in Brazil, it is worthwhile to investigate the intensity of young firms across sectors. The construction industry has the most new firms and the fewest firms between 6 and 10 years old. The mining and health care industries have the lowest share of new firms and have among the lowest shares of firms between 6 and 10 years old. Over all industries, we see a consistent pattern that the highest share of firms within all industries are age 1 to 5.
Figure 1.16: Intensity of Young Firms by Industry: Brazil, 2005-2013

Notes: RAIS data, 2005 - 2013. Share of young firms in each industry in three different age categories. Industries are sorted by the share of new firms.

Figure S3 shows the share of single-establishment firms and multi-establishment firms for each industry in Brazil. The first bar for each figure shows the share of single-establishment firms and the second bar shows the share of multi-establishment firms. Agriculture and utilities have the highest share of multi-establishment firms, whereas the accommodation and food services sector has the lowest share of multi-establishment firms. Across all sectors, the overwhelming majority of firms only own a single establishment.
Notes: RAIS data, 2005 - 2013. Percentage of single-establishment and multi-establishment firms by industry. Industries are sorted by share of multi-establishment firms.

1.7.4 Up-or-Out Dynamics by Sector

The main analysis showed the importance of the up-or-out dynamic of employment for the Brazilian labor market. Here, we repeat that analysis by broad sectors to see if any one sector in the Brazilian economy is driving our result. Figure S4 shows the pattern to be consistent across sectors in Brazil. That is, firm start-ups create a lot of jobs, but many start-ups fail. However, the firms that survive, grow very fast.
Notes: RAIS data, 2005 - 2013. In the top panel, the figure shows estimates for one-way models of firm growth rates by firm age class and firm growth rates by firm age class and firm size class (using both base size and average size). A higher value in the top panel indicates that a particular firm age class has a higher employment growth rate relative to other firm age classes. In the bottom panel, the figure shows the estimates for one-way models of firm exit by firm age class and estimates for two-way models of firm exit by firm age class and firm size class (using both base size and average size). A higher value in the bottom panel indicates that a particular firm age class has a higher firm exit rate relative to other firm age classes.
1.7.5 Employment Volatility for Continuing Firms Only

In this section, we present the results for employment volatility by firm size and firm age for the subset of continuing firms only. We use the worker reallocation rate to measure employment volatility.
Figure 1.19: Worker Reallocation Rates by Firm Size and Firm Age, Continuing Firms Only

(a) By Firm Size

(b) By Firm Age

Notes: RAIS data, 2005 - 2013. In the top panel, the figure shows estimates for one-way models of firm worker reallocation rates by firm size class and worker reallocation rates by firm size class and firm age class (using both base size and average size) for continuing firms only. In the bottom panel, the figure shows the estimates for one-way models of worker reallocation rates by firm age class and estimates for two-way models of worker reallocation rates by firm age class and firm size class (using both base size and average size) for continuing firms only. A higher value indicates that a particular firm size or age class has a higher worker reallocation rate relative to other firm size or age classes.
1.7.6 Inclusion of industry and year effects

In this section, we repeat our main analyses but now include both year and industry effects. The reference category is then constructed to account for the share of the data in each year and industry. Figures S5 - S14 show very similar results to those in Figures 4 - 14 in the text.

Figure 1.20: Employment Growth Rate and Firm Size, with Year and Industry Effects

Notes: RAIS data, 2005 - 2013. The figure shows estimates for one-way models of employment growth by firm size class and estimates for two-way models of employment growth by firm size class controlling for firm age class (using both base size and average size). All models include industry and year controls. A higher value indicates that a particular firm size class has a higher firm growth rate relative to other firm size classes.
Figure 1.21: Firm Exit by Firm Size, with Year and Industry Effects

Notes: RAIS data, 2005 - 2013. The figure shows estimates for one-way models of firm exit by firm size class and for two-way models of job destruction due to firm exit by firm size class controlling for firm age class. All models include industry and year controls. A higher value indicates that a particular firm size class has a higher firm exit rate relative to other firm size classes.
Figure 1.22: Employment Growth Rate and Firm Age, with Year and Industry Effects

Notes: RAIS data, 2005 - 2013. The figure shows estimates for one-way models of employment growth by firm age class and estimates for two-way models of employment growth by firm age class controlling for firm size class (using both base size and average size). All models include industry and year controls. A higher value indicates that a particular firm age class has a higher firm growth rate relative to other firm age classes. Results for new firms are not displayed.
Figure 1.23: Firm Exit by Firm Age, with Year and Industry Effects

Notes: RAIS data, 2005 - 2013. The figure shows estimates for one-way models of firm exit by firm age class and for two-way models of job destruction due to firm exit by firm age class controlling for firm size class (using both base size and average size). All models include industry and year controls. A higher value indicates that a particular firm age class has a higher firm exit rate relative to other firm age classes. New firms are excluded from the figure because they cannot destroy any jobs by construction.
Figure 1.24: Worker Reallocation Rate by Firm Size, with Year and Industry Effects

Notes: RAIS data, 2005 - 2013. The figure shows estimates for one-way models of worker reallocation rates by firm size class and estimates for two-way models of worker reallocation rates by firm size class controlling for firm age class (using both base size and average size). All models include industry and year controls. A higher value indicates that a particular firm size class has a higher firm churn rate relative to other firm size classes.
Figure 1.25: Worker Reallocation Rate by Firm Age, with Year and Industry Effects

Notes: RAIS data, 2005 - 2013. The figure shows estimates for one-way models of worker reallocation rates by firm age class and estimates for two-way models of worker reallocation rates by firm age class controlling for firm size class (using both base size and average size). All models include industry and year controls. A higher value indicates that a particular firm age class has a higher firm churn rate relative to other firm age classes.
Figure 1.26: Stable Employment Growth by Firm Size (Tenure), with Year and Industry Effects

Notes: RAIS data, 2005 - 2013. The figure shows estimates for one-way models of stable employment growth (tenure) by firm size class and estimates for two-way models of stable employment growth (tenure) by firm size class controlling for firm age class (using both base size and average size). All models include industry and year controls. A higher value indicates that a particular firm size class has a higher stable growth rate relative to other firm size classes.
Figure 1.27: Stable Employment Growth by Firm Size (Retention), with Year and Industry Effects

Notes: RAIS data, 2005 - 2013. The figure shows estimates from one-way models of stable employment growth (retention) by firm size class and estimates for two-way models of stable employment growth (retention) by firm size class controlling for firm age class (using both base size and average size). All models include industry and year controls. A higher value indicates that a particular firm size class has a higher stable growth rate relative to other firm size classes.
Figure 1.28: Stable Employment Growth by Firm Age (Tenure), with Year and Industry Effects

Notes: RAIS data, 2005 - 2013. The figure shows estimates from one-way models of stable employment growth (tenure) by firm age class and estimates for two-way models of stable employment growth (tenure) by firm age class controlling for firm size class (using both base size and average size). All models include industry and year controls. A higher value indicates that a particular firm age class has a higher stable growth rate relative to other firm age classes.
Figure 1.29: Stable Employment Growth by Firm Age (Retention), with Year and Industry Effects

Notes: RAIS data, 2005 - 2013. The figure shows estimates from one-way models of stable employment growth (retention) by firm age class and estimates for two-way models of stable employment growth (retention) by firm age class controlling for firm size class (using both base size and average size). All models include industry and year controls. A higher value indicates that a particular firm age class has a higher stable growth rate relative to other firm age classes.
1.7.7 Inclusion of short-lived firms

In this section, we repeat the job creation and job destruction analysis of Section 5.1
above, but now include short-lived firms. The data used by HJM does not capture firms
that exist for less than 1 year, so our main analysis excluded these firms for consistency.
These short-lived firms are firms which appear in our data, but did not have any workers
with non-zero wages in December. Figures S15 - S18 correspond to Figures 4 - 7 in the text
and we find very similar results to those for our main analysis. We only repeat the analysis
for Section 5.1 because the employment volatility and job stability analysis in the text
already include short-lived firms in the analysis.
Table 1.4: Summary Statistics including Short-Lived Firms

<table>
<thead>
<tr>
<th>Establishment Level</th>
<th>count</th>
<th>mean</th>
<th>sd</th>
</tr>
</thead>
<tbody>
<tr>
<td>New Establishment</td>
<td>21,907,534</td>
<td>0.14</td>
<td>0.35</td>
</tr>
<tr>
<td>Continuing Establishment</td>
<td>21,907,534</td>
<td>0.75</td>
<td>0.44</td>
</tr>
<tr>
<td>Destroyed Establishment</td>
<td>21,907,534</td>
<td>0.12</td>
<td>0.32</td>
</tr>
<tr>
<td>Employment</td>
<td>21,907,534</td>
<td>11.02</td>
<td>79.55</td>
</tr>
<tr>
<td>Base Size</td>
<td>21,907,534</td>
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<td>78.06</td>
</tr>
<tr>
<td>Average Size</td>
<td>21,907,534</td>
<td>10.35</td>
<td>76.22</td>
</tr>
<tr>
<td>Age</td>
<td>21,907,534</td>
<td>5.98</td>
<td>6.23</td>
</tr>
<tr>
<td>Employment Growth Rate</td>
<td>21,907,534</td>
<td>0.06</td>
<td>1.08</td>
</tr>
<tr>
<td>Worker Reallocation Rate</td>
<td>19,208,937</td>
<td>1.81</td>
<td>13.52</td>
</tr>
<tr>
<td>Separation Rate</td>
<td>19,208,937</td>
<td>0.76</td>
<td>7.98</td>
</tr>
<tr>
<td>Stable Employment Growth Rate (Tenure)</td>
<td>21,752,475</td>
<td>0.59</td>
<td>1.29</td>
</tr>
<tr>
<td>Stable Employment Growth Rate (Retention)</td>
<td>13,399,544</td>
<td>-0.15</td>
<td>0.99</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Firm Level</th>
<th>count</th>
<th>mean</th>
<th>sd</th>
</tr>
</thead>
<tbody>
<tr>
<td>Num. of Establishments</td>
<td>19,302,806</td>
<td>1.13</td>
<td>6.14</td>
</tr>
<tr>
<td>New Firm</td>
<td>19,302,806</td>
<td>0.14</td>
<td>0.34</td>
</tr>
<tr>
<td>Continuing Firm</td>
<td>19,302,806</td>
<td>0.75</td>
<td>0.43</td>
</tr>
<tr>
<td>Destroyed Firm</td>
<td>19,302,806</td>
<td>0.11</td>
<td>0.31</td>
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<td>Employment</td>
<td>19,302,806</td>
<td>12.50</td>
<td>194.45</td>
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<tr>
<td>Base Size</td>
<td>19,302,806</td>
<td>12.13</td>
<td>187.51</td>
</tr>
<tr>
<td>Average Size</td>
<td>19,302,806</td>
<td>11.82</td>
<td>188.36</td>
</tr>
<tr>
<td>Age</td>
<td>19,302,806</td>
<td>5.85</td>
<td>5.84</td>
</tr>
<tr>
<td>Employment Growth Rate</td>
<td>19,302,806</td>
<td>0.06</td>
<td>1.07</td>
</tr>
<tr>
<td>Worker Reallocation Rate</td>
<td>19,149,889</td>
<td>1.61</td>
<td>8.15</td>
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<tr>
<td>Separation Rate</td>
<td>19,149,889</td>
<td>0.72</td>
<td>4.54</td>
</tr>
<tr>
<td>Stable Employment Growth Rate (Tenure)</td>
<td>14,894,950</td>
<td>-0.24</td>
<td>0.82</td>
</tr>
<tr>
<td>Stable Employment Growth Rate (Retention)</td>
<td>11,373,559</td>
<td>-0.08</td>
<td>0.94</td>
</tr>
</tbody>
</table>

Notes: RAIS data, 2005 - 2013. Summary statistics for the establishment-level data in the upper panel and for the firm-level data in the lower panel.
Figure 1.30: Employment Growth Rate and Firm Size including Short-Lived Firms

Notes: RAIS data, 2005 - 2013. The figure shows estimates for one-way models of employment growth by firm size class and estimates for two-way models of employment growth by firm size class controlling for firm age class (using both base size and average size). A higher value indicates that a particular firm size class has a higher firm growth rate relative to other firm size classes.
Figure 1.31: Firm Exit by Firm Size including Short-Lived Firms

Notes: RAIS data, 2005 - 2013. The figure shows estimates for one-way models of firm exit by firm size class and for two-way models of firm exit by firm size class controlling for firm age class. A higher value indicates that a particular firm size class has a higher firm exit rate relative to other firm size classes.
Figure 1.32: Employment Growth Rate and Firm Age including Short-Lived Firms

Notes: RAIS data, 2005 - 2013. The figure shows estimates for one-way models of employment growth by firm age class and estimates for two-way models of employment growth by firm age class controlling for firm size class (using both base size and average size). A higher value indicates that a particular firm age class has a higher firm growth rate relative to other firm age classes. Results for firm-births are not displayed.
Figure 1.33: Firm Exit by Firm Age including Short-Lived Firms

Notes: RAIS data, 2005 - 2013. The figure shows estimates for one-way models of firm exit by firm age class and for two-way models of firm exit by firm age class controlling for firm size class (using both base size and average size). A higher value indicates that a particular firm age class has a higher firm exit rate relative to other firm age classes. New firms are excluded from the figure because they cannot destroy any jobs by construction.
CHAPTER 2

THE EFFECTS OF A TRADE SHOCK ON GENDER-SPECIFIC LABOR MARKET OUTCOMES IN BRAZIL

2.1 Introduction

The world economy continues to become more integrated as countries increase their exposure to international trade. Brazil is one of many countries to experience a drastic trade liberalization episode as a means to create sustainable economic growth. The country liberalized their trade policies in the early 1990’s and experienced an increase in trade values as a direct result. However, Brazil’s trade values began to increase at an even higher rate in the early 2000’s, which corresponds to China’s accession to the World Trade Organization (WTO) in 2001. Brazil’s reliance on trade with China has consistently increased since. In 2001, Brazil’s imports from China and exports to China accounted for approximately 3% and 4% of Brazil’s total imports and exports, respectively. By 2013, nearly 23% of Brazil’s total exports and 15% of its total imports were to or from China.\(^1\) Economists have long been interested in studying the impact of increased international trade on economic outcomes in countries around the world. China’s rapid economic growth and expansion into world trade markets further peaked economists’ interest, leading to the emergence of a literature that focuses specifically on the economic impacts of China’s rise.

In this paper, I analyze the impact of the China trade shock on gender-specific local labor market outcomes in Brazil. The analysis combines matched employer-employee data for the entire formal labor market in Brazil for the years 2004-2013 with UN Comtrade data for the years 2008-2013. I use Autor, Dorn, and Hanson’s (2013) instrumental variable

\(^{1}\)Brazil’s trade with China as a share of Brazil’s GDP also increases over the sample for both exports to and imports from China.
approach to measure the impact of both increased imports from China and increased exports to China on male and female local labor market outcomes in Brazil. In contrast to the United States, Brazil experienced a surge in exports to China nearly equal to the surge in imports from China.\textsuperscript{2} Thus, analyzing the effects of both imports from and exports to China is more appropriate for the case of Brazil. This paper contributes to two branches of the trade and labor literature. First, it contributes to the literature on the gender-specific effects of trade by determining whether the China trade shock can improve females’ relative labor market outcomes. Second, it contributes to the emerging literature on the rise of China by examining the impact of both imports from and exports to China on local labor market outcomes in a fellow emerging country.

Brazil provides an interesting context to study the impacts of the China trade shock for several reasons. As previously mentioned, Brazil has a relatively balanced trade relationship with China and often runs a trade surplus. This pattern is consistent for several other emerging and developing countries (Costa, Garred, & Pessoa, 2016). Therefore, findings on China’s impact on Brazil are likely applicable to several other developing countries with similar trade patterns. Further, Brazil and China are both considered emerging global economies. Brazil is the largest emerging economy in the Western Hemisphere while China is the largest in the Eastern Hemisphere (Pereira & de Castro Neves, 2011). Additionally, out of 75 countries, Di Giovanni, Levchenko, and Zhang (2014) rank Brazil as the fifth most similar country to China in regards to technology. Therefore, the aggregate effect of increased trade with China on a fellow emerging country of similar size and endowments should be of interest to policy makers in these countries.

There are three potential reasons to expect increased trade to have gender-specific effects. The first reason relates to the pro-competitive effects of trade. In theory, international trade increases the level of competition domestic firms face, which reduces firms’ ability to discriminate in hiring practices (Black & Brainerd, 2004). A second reason

\textsuperscript{2}Imports from China grew by approximately 900% and exports to China grew by approximately 750% from 2004 to 2013. (Author calculations using UN Comtrade data).
related to the pro-competitive effects of trade centers on the idea that trade induces technical change. If technical change is skill-biased, then some research indicates that skill-biased technical change can have gender implications. As firms upgrade their technology, some tasks become more complementary to female workers (Juńh, Ujhelyi, & Villegas-Sanchez, 2014). The third reason for gender-specific effects of trade relates to labor market segregation and reallocation. Males and females often segregate into certain occupations or industries. For the case of Brazil, females are most represented in the non-traded sector. This implies that the impacts of trade will likely be stronger for males in traded sectors (Gaddis & Pieters, 2017).

The results indicate that increased exports to China are associated with positive female employment gains in both the traded and non-traded sectors in Brazil. This directly translates to an increase in the share of female employment in both sectors. Female employment gains are very large, between 10 and 20 percentage points for the average microregion, and of economic significance. Exports to China also increase female wage growth in the traded sector while imports from China increase female wage growth in the non-traded sector. Female wage gains are smaller than the employment gains, between 1 and 2 percentage points, but they do reflect real wage growth. Occupation segregation also declines in response to increased trade with China in both sectors; the average microregion experienced declines in occupation segregation between 0.5 and 2 percentage points. Since occupation segregation is often considered a persistent reason for continued gender gaps, these declines are of economic importance despite being small in magnitude. When the analysis is broken down by skill, only high-skilled males benefit from increased trade with China while both low- and high-skilled females benefit from increased trade with China.

Trade with China is complementary to female employment and provides

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3Low-skill male workers are traditionally favored for blue-collar manufacturing jobs due to strength requirements associated with manual labor. As manual labor tasks are automated and replaced with technology, women become better suited for these jobs.

4A microregion represents a local labor market in Brazil. A formal definition of a microregion is presented in Section 2.4.
employment opportunities for females in both the traded and non-traded sector. The results support the mechanisms of skill-biased technical change and labor market segregation and reallocation. As firms are more exposed to international trade, it is possible that they upgrade their technology, which makes some tasks more suitable for female employees. However, the results also indicate that trade has gender-specific impacts through labor market segregation and reallocation. Trade with China impacts female employment and wages in the non-traded sector, where females are more represented. This could translate to females more easily gaining employment in the non-traded sector. The declines in occupation segregation also lend support to the labor segregation and reallocation mechanism. Trade with China breaks down some labor segregation barriers, which leads some females to enter male-dominated occupations (or visa versa). While the negative effects of Chinese imports on manufacturing labor market outcomes in the US are well known (Autor et al., 2013), this paper highlights the potential for positive effects of the China trade shock in other countries. This is particularly true for countries that have a more balanced trade relationship with China.

This paper proceeds as follows. Section 2.2 presents an overview of the related literature. Section 2.3 summarizes Brazil’s trade history and trade relationship with China. Section 2.4 details the methodology and Section 2.5 describes the data. Section 2.6 summarizes the results. Section 2.7 offers concluding remarks.

### 2.2 Literature Review

With the rise of globalization and adoption of trade openness policies around the world, economists have become increasingly interested in studying the impacts of international trade on subsequent economic and labor market outcomes.⁵ This paper is

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⁵Previous research studies the link between international trade and employment, wage inequality, labor market discrimination, child labor, crime, and poverty, among many other outcomes. See Autor et al. (2013), Borjas and Ramey (1995), Black and Brainerd (2004), Edmonds, Pavcnik, and Topalova (2010), Dix-Carneiro, Soares, and Ulyssea (2017), and Hasan, Mitra, and Ural (2006), respectively.
closely related to two branches of the trade and labor literature. First, it adds to the 
literature on the gender-specific impacts of trade by determining how trade shocks affect 
women’s relative local labor market position. This paper also contributes to the emerging 
literature on the economic impacts of China’s rise in world trade markets. While most 
research focuses on the effects of increased imports from China, the analysis accounts for 
both increased imports from and increased exports to China.

2.2.1 Gender-Specific Impacts of Trade

One potential mechanism for trade to have gender-specific labor market effects 
centers around Becker’s (1957) model of taste-based discrimination. Black and Brainerd 
(2004) test Becker’s hypothesis that increased trade, a proxy for competition, should drive 
out labor market discrimination. The authors analyze CPS data for 1977 to 1994 and find 
some evidence that increased imports decrease the ability of firms to discriminate. 
Increased import shares decreased the residual gender wage gap in initially concentrated 
industries, but increased the residual gender wage gap in initially competitive industries.\(^6\) 
Kongar (2007) extends Black and Brainerd’s (2004) work and finds that declines in the 
gender wage gap stem from an increase in average female wages due to low-wage female 
workers losing their jobs.

Evidence on the impact of globalization on gender discrimination for countries 
beyond the US is mixed. Artecona and Cunningham (2002) do not find any significant 
effect of Mexico’s trade liberalization on the gender wage gap for the years 1987 to 1993. 
Studies for Taiwan, Korea, and Japan all indicate that increased competition from foreign 
trade actually increased the gender wage gap (see Berik, Rodgers, and Zveglich (2004) for 
Taiwan and Korea and Kucera (2001) for Japan). In contrast, studies for Germany and 
Vietnam find that increased trade decreased the gender wage gap (see Kucera (2001) for 
the China trade shock and the gender wage gap in Brazil is the most relevant study for this

\(^6\)The authors define an industry as concentrated if the four-firm concentration ratio was 0.40 or greater 
in 1977, the first year in the data, and this definition is held constant over the sample period.

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The authors determine that increased imports from China decreased the gender wage gap in Brazil from 2000 to 2010. However, the declines in the gender wage gap are attributed to improvements in occupation composition rather than discrimination. In this paper, I extend Benguria and Ederington’s (2017) project to analyze the impact of both imports from China and exports to China on gender-specific local labor market outcomes, which accounts for Brazil’s relatively balanced trade relationship with China.

A second mechanism through which trade can have gender-specific labor market effects relates to the idea that trade induces technical change. Since technical change is often skill-biased it can have gender implications if technology upgrades lower the need for physically demanding skills. Juhn et al. (2014) study whether trade liberalization in Mexico reduced gender inequality via technology upgrades. Their findings indicate that trade liberalization improved females’ relative employment and wages in blue-collar, manufacturing jobs. The authors conclude that exports are most associated with technological upgrades, which are complementary to female employment. Other studies have linked export growth to technological advancement, but they do not study any gender implications. For example, Liu, Pang, and Kong (2017) determine that export growth in China is positively associated with technological innovation.

Trade can also differentially impact local labor market outcomes by gender due to the persistence of labor segregation and labor reallocation. Gender segregation into specific industries or occupations remains high in most countries and remains one of the reasons for persistent gender gaps (Blau, Brummund, & Liu, 2013). For the case of Brazil, females are most represented in non-traded sectors. This pattern suggests that males are most likely to experience stronger impacts from trade. Gaddis and Pieters’ (2017) study this mechanism for Brazil’s trade liberalization. Their results indicate that liberalization decreased labor force participation and employment rates for both men and women, but males experienced larger declines. Gaddis and Pieters’ (2017) results are concentrated in the low-skilled.

7For an overview of the literature on the gender wage gap in Brazil see Garcia, Nopo, and Salardi (2009).
8This closely relates to the "brains" vs. "brawn" explanation in footnote 2.
population, particularly low-skilled female employment in the traded sector. They conclude that Brazil’s trade liberalization did not improve the relative position of women in Brazil.

In this paper, I build upon the existing literature and determine whether the China trade shock improves females’ relative local labor market position and if so, through which mechanism. This paper is similar in spirit to Gaddis and Pieters’ (2017), but I use a different data set, study a different, more recent trade shock, and analyze local labor market outcomes beyond employment. This paper is also similar to Benguria and Ederington’s (2017) work, but I analyze both channels of the China trade shock and analyze females’ relative employment position. It is important to analyze both imports and exports for Brazil’s trade with China since Brazil typically runs a trade surplus with China. Further, it is necessary to analyze both aggregate gender-specific outcomes and relative labor market outcomes to determine whether trade truly improves females’ position or if the improvement stems from trade harming male outcomes.

2.2.2 Economic Impacts of China’s Growth

There is also an emerging literature that focuses specifically on the economic impacts of China’s rise to become a world trading power. This area of research, pioneered by Autor et al. (2013), is also referred to as the “China trade shock”. Autor et al. (2013) study the impact of increased manufacturing imports from China on US local labor market outcomes for the years 1990 to 2007. The authors find that manufacturing workers employed in commuting zones more exposed to increased manufacturing imports from China experienced lower wages, lower labor force participation rates, higher unemployment rates, and higher government transfer payments relative to workers employed in commuting zones less exposed to imports from China. Their study highlights the interesting case study China provides due to China’s unprecedented economic growth, an economic shock felt by countries around the world. It also introduced an instrumental variable that is uniquely
appropriate for measuring China’s supply-driven growth.\textsuperscript{9} Pierce and Schott (2016) also link the decline of US manufacturing employment to trade with China.\textsuperscript{10}

The literature to date generally finds that increased imports from China (dominantly manufacturing imports) harm manufacturing workers in partner countries, confirming that the “China trade shock” has been felt worldwide.\textsuperscript{11} However, only analyzing the impact of increased imports from China ignores an important aspect of China’s growth. While China’s rise was supply driven due to their ongoing transition from a central planning to a market-based economy, the consumer base within China also rapidly increased, increasing China’s demand for imports as well. China’s decreasing trade costs simultaneously made exporting goods to other countries and importing goods from other countries much easier. A smaller branch of the literature focuses on both the supply side of increased imports from China and the demand side of increased exports to China.

For example, Brazilian microregions more exposed to increased manufacturing imports from China experienced slower wage growth, but microregions more exposed to increased commodity exports to China experienced faster wage growth from 2000 to 2010 (Costa et al., 2013). A recent study by Dauth et al. (2014) analyzes the impact of increased trade with China and Eastern Europe on German labor market outcomes for the years 1988 to 2008. The authors find that German regions specializing in import-competing industries experienced substantial job losses, but regions specializing in export-competing industries experienced large employment gains. Overall, Dauth et al. (2014) determine that increased trade with the East resulted in net employment gains (slower employment decline) in Germany, but attributed the net gains to the rise of Eastern Europe. In this paper, I contribute to the emerging literature on China’s rise,\textsuperscript{12}

\textsuperscript{9}Details on Autor et al.’s (2013) instrumental variable approach are included in the methodology section. The authors also study the link between increased imports from China and political polarization (Autor, Dorn, Hanson, & Majlesi, 2016) and innovation (Autor, Dorn, Hanson, Pisano, & Shu, 2016) in separate papers.
\textsuperscript{10}Pierce and Schott use the elimination of uncertain bilateral tariffs between the US and China, a trade policy change associated with China’s accession to the WTO, for identification.
\textsuperscript{11}See Mion and Zhu (2013) for Belgium, Dauth, Findeisen, and Suedekum (2014) for Germany, Costa et al. (2013) for Brazil, and Iacovone, Rauch, and Winters (2013) for Mexico.
accounting for the effect of both the supply and demand components of the China trade shock. This paper determines an additional channel through which the China trade shock has positive effects via improving females’ local labor market outcomes.

2.3 Brazil’s Trade History and Trade with China

Through the 1980’s Brazil largely closed off its economy to international trade via import substitution industrialization (ISI) policies. The ISI policies promoted domestic production over foreign imports through extremely high protectionist measures, which included extremely high import tariffs, a long list of prohibited imports, and numerous “special customs regimes”. In the early 1990’s Brazil abandoned their ISI policies in favor of more open trade policies in hopes of creating more sustainable economic growth. Subsequently, the long list of prohibited imports and most non-tariff barriers were eliminated and import tariffs were drastically reduced (Dix-Carneiro & Kovak, 2017a). Kovak (2013) and Dix-Carneiro and Kovak (2017a) both analyze the impact of Brazil’s trade liberalization in the early 1990’s on subsequent local labor market dynamics in Brazil. The authors exploit changes in import tariffs and determine that Brazilian workers employed in microregions more exposed to liberalization experienced consistent declines in formal sector employment and wages.

Brazil’s trade liberalization was largely complete by 1995 and the country has continuously increased it’s exposure to international trade since. Figure 2.3 in the appendix shows Brazil’s total trade values with the rest of the world (Panel A) and total trade values with China (Panel B) for the years 1992-2013. From 1992 to 2013, the value of total imports to Brazil and exports from Brazil both increased from less than $50 billion to almost $250 billion. The pattern is similar for Brazil’s trade with China. The vertical line

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12The special customs regimes granted preferred access to certain types of imports by eliminating or reducing the import tariffs for specific countries (Kovak, 2013).
13See Kovak (2013) or Dix-Carneiro and Kovak (2017a) for a detailed history of Brazil’s trade liberalization.
Figure 2.1: Brazil’s Share of Total Trade with China, 1992-2013

![Graph showing Brazil's Share of Total Trade with China, 1992-2013](image)

Notes: UN Comtrade data, 1992-2013. The vertical line at the year 2001 indicates the year China officially joined the WTO.

On both graphs corresponds to the year 2001, which is the year China officially joined the WTO. For both Brazil’s trade with the rest of the world and trade with China, the rate of increased trade becomes much sharper beginning in the early 2000’s. During the 2000’s, Brazil also experienced an economic boom, which could partially explain rising trade values. Economic growth began to slow in 2011, signaling Brazil’s eventual economic recession, which officially began in 2015.

Figure 2.3 clearly shows that Brazil increased its exposure to international trade with the world and with China specifically. Of arguably more importance though is China’s increasing share of Brazil’s total trade values. Figure 2.1 plots China’s share of Brazil’s total trade for the years 1992 through 2013. In 1992, approximately 1% of Brazil’s total imports originated in China and approximately 2% of Brazil’s total exports were
exported to China. By 2013, these numbers jumped to 15% for imports and nearly 23% for exports.\textsuperscript{14} This indicates that China has become an increasingly important trading partner for Brazil. In fact, China became Brazil’s top trading partner for imports in 2012 and for exports in 2009.\textsuperscript{15}

Brazil’s trade relationship with China can generally be categorized by manufacturing imports and commodity exports. Nearly all of Brazil’s imports (98.7%) from China are in the manufacturing sector. Brazil’s exports to China are split between the agriculture and forestry (37%), mining and quarrying (48%), and manufacturing (15%) sectors.\textsuperscript{16} Tables 2.10 and 2.11 in the appendix list the 20 industries with the largest share of total imports from and exports to China, respectively, for the year 2013. Industry shares for imports are spread out over several manufacturing industries. Nearly 10% of imports from China are in the manufacture of office, accounting, and computing machinery, 7% of imports from China are in the manufacture of TV and radio receivers, sound or video recording or reproducing apparatus, and 6% are in the manufacture of basic chemicals. In contrast, the industry shares for exports to China are extremely concentrated. Almost 40% of total exports to China are in the mining of iron ores and 36% of total exports to China are in the growing of crops, market gardening, and horticulture.

2.4 Methodology

Early research typically studied the impact of international trade on industry- or firm-level outcomes.\textsuperscript{17} In this paper, I follow the more recent approach and study the

\textsuperscript{14}This relationship is also robust to using Brazil’s trade with China as a share of Brazil’s GDP, which is presented in Panel B of Figure 2.4 in the appendix. While the numbers are smaller in magnitude, the sharp increase in the early 2000’s remains for both imports from and exports to China.

\textsuperscript{15}World Integrated Trade Solution Trade Data for Brazil.

\textsuperscript{16}Author calculations using UN Comtrade data for the year 2013.

impact of international trade on local labor market outcomes.\textsuperscript{18} Studying local labor markets in Brazil is appropriate because regional mobility in Brazil is limited; therefore, worker’s labor market opportunities are mostly confined to their specific regional location (Dix-Carneiro, 2014). I define a local labor market in Brazil as a microregion.\textsuperscript{19} Other territorial units in Brazil defined by the IBGE (Brazilian Institute for Geography and Statistics) include: (in order of increasing size) municipalities, microregions, mesoregions, states, and regions. A microregion is similar to a commuting zone in the United States in the sense that it is larger than a single municipality but smaller than a state.

I follow the methodology of Autor et al. (2013) as closely as possible to measure Brazil’s Chinese import exposure and extend their methodology to account for Brazil’s Chinese export exposure. Since the analysis uses microregions in Brazil as the unit of analysis, the trade variables must also measure trade exposure at the microregion level. The change in Chinese import exposure per worker in Brazil \( b \) for microregion \( i \) in year \( t \) is defined as follows:

\[
\Delta IPW_{bit} = \sum_j \frac{L_{ijt}}{L_{bjt}} \frac{\Delta M_{bcjt}}{L_{it}},
\]

where \( L_{ijt} \) is employment in microregion \( i \) in industry \( j \) in year \( t \), \( L_{bjt} \) is national employment in industry \( j \) in year \( t \) in Brazil \( b \), and \( L_{it} \) is total employment in microregion \( i \) in year \( t \). \( \Delta M_{bcjt} \) is the change in imports from China \( c \) to Brazil \( b \) in industry \( j \) from year \( t \) to year \( t+1 \).\textsuperscript{20} The change in Chinese import exposure per worker measure is the sum of Brazil’s imports from China across all industries, weighted by the initial industry and microregion employment shares. Therefore, the variation in the change in Chinese import exposure variable comes directly from different employment levels across microregions, \( i \),

\textsuperscript{18}Using local labor markets as the unit of analysis was made popular by Topalova (2007). Other papers to use local labor markets as the unit of analysis include Autor et al. (2013), Kovak (2013), Dix-Carneiro and Kovak (2017a), Costa et al. (2013), and McCaig (2011), among others.

\textsuperscript{19}Other papers that define a local labor market in Brazil as a microregion include Dix-Carneiro and Kovak (2017a), Kovak (2013), Gaddis and Pieters (2017), Costa et al. (2013), and Benguria and Ederington (2017).

\textsuperscript{20}Equation (2.1) is analogous to Equation (3) in Autor et al. (2013).
and industries, \( j \), in Brazil.

A common identification problem in the trade and labor literature is that labor market outcomes are considered endogenous to international trade. One explanation for this is that Brazil’s trade with China and labor market outcomes could both be correlated with a third, unobserved variable, such as changing consumer demand within Brazil. Given Brazil’s economic boom during the 2000’s, which is largely attributed to increased household consumption, this is a valid threat to the identification strategy. If internal supply and demand factors in Brazil contributed to Brazil’s increased trade with China, then the change in import exposure per worker variable is endogenous and OLS estimates will be biased. In order to identify the causal effect of increased trade with China on local labor market outcomes, I use the instrumental variable made popular by Autor et al. (2013). The idea is to instrument for Brazil’s trade with China using other countries’ trade with China.\(^{21}\) The identification strategy assumes that China’s growth in world trade markets is largely supply driven. In other words, countries increased their trade with China due to changing economic conditions in China, such as decreased trade costs as China transitioned to a market-based economy, rather than changing demand factors within other countries. If this assumption does not hold, then estimates of the impact of increased Chinese import exposure will likely underestimate the actual effect (Autor et al., 2013).

The instrumental variable, the change in Chinese import exposure per worker in other countries, is calculated as follows:

\[
\Delta IPW_{oit} = \sum_j \frac{L_{ijt-1} \Delta M_{ocjt}}{L_{bjt-1} L_{it-1}},
\]

where \( L_{ijt-1} \) measures the employment in microregion \( i \) in industry \( j \) from the start of the previous period \( t-1 \), \( L_{bjt-1} \) is national employment in industry \( j \) in Brazil \( b \) from the start of the previous period \( t-1 \), and \( L_{it-1} \) is total employment in microregion \( i \) from the start of

\(^{21}\)Autor et al. originally used this IV for the United States’ trade with China. The authors used other developed countries increased imports from China to instrument for US increased imports from China.
the previous period $t-1$. $\Delta M_{ocjt}$ measures the change in imports from China $c$ to other countries $o$ in industry $j$ from year $t$ to year $t+1$. The instrumental variable uses lagged employment levels to account for the possibility that employment changes in Brazil were in response to anticipated increased imports from China.

I extend Autor et al.’s (2013) method to also account for exports to China. The change in Chinese export exposure per worker in Brazil $b$ for microregion $i$ in year $t$ is calculated as follows:

$$\Delta EPW_{bit} = \sum_j \frac{L_{ijt}}{L_{bjt}} \frac{\Delta E_{bcjt}}{L_{it}}, \quad (2.3)$$

where $L_{ijt}$, $L_{bjt}$, and $L_{it}$ are previously defined in equation (2.1) and $\Delta E_{bcjt}$ is the change in exports to China $c$ from Brazil $b$ in industry $j$ from year $t$ to year $t+1$. Again, the variation in the export exposure measure stems directly from different industry $j$ and microregion $i$ employment structures in Brazil.

However, endogeneity issues are also likely to confound the change in Chinese export exposure measure. Therefore, I also extend Autor et al.’s (2013) instrumental variable approach to account for exports. Instrumenting for Brazil’s growth in exports to China with other countries’ growth in exports to China relies on the assumption that increased exports to China were also driven by changing economic conditions in China (increased demand for products in China due to a larger consumer base and decreasing trade costs). The instrumental variable, the change in Chinese export exposure per worker in other countries, is calculated as follows:

$$\Delta EPW_{oit} = \sum_j \frac{L_{ijt-1}}{L_{bjt-1}} \frac{\Delta E_{ocjt}}{L_{it-1}}, \quad (2.4)$$

where $L_{ijt-1}$, $L_{bjt-1}$, and $L_{it-1}$ are previously defined in equation (2.2). $\Delta E_{ocjt}$ measures the

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22 Equation (2.2) matches equation (4) in Autor et al. (2013).
23 Import IV countries include: Argentina, Chile, Colombia, Indonesia, Peru, South Africa, Thailand, and Uruguay.
change in exports to China $c$ from other countries $o$ in industry $j$ from year $t$ to $t+1$.\textsuperscript{24} The instrumental variable again uses lagged employment levels to account for the possibility that labor market outcomes in Brazil shifted in response to anticipated trade changes.

I use a two stage least squares (2SLS) model with two instrumental variables for all analyses. The model takes the following form:

$$\Delta Y_{it} = \alpha_0 + \beta_0 \Delta \hat{IPW}_{bit} + \gamma_0 \Delta \hat{EPW}_{bit} + \lambda_0 X_{it} + \epsilon_{it},$$

(2.5)

where the first stage models are estimated as follows:

$$\Delta \hat{IPW}_{bit} = \alpha_1 + \beta_1 \Delta IPW_{oit} + \gamma_1 \Delta EPW_{oit} + \lambda_1 X_{it} + \epsilon_{it},$$

(2.6)

$$\Delta \hat{EPW}_{bit} = \alpha_2 + \beta_2 \Delta IPW_{oit} + \gamma_2 \Delta EPW_{oit} + \lambda_2 X_{it} + \epsilon_{it}.$$  

(2.7)

$\Delta Y_{it}$ is the change or growth in various local labor market outcomes in microregion $i$ from year $t$ to year $t+1$, $\Delta IPW_{bit}$, $\Delta IPW_{oit}$, $\Delta EPW_{bit}$, and $\Delta EPW_{oit}$ are defined by equations (2.1), (2.2), (2.3), and (2.4), respectively, and $X_{it}$ is a vector of microregion specific control variables from the start of the period $t$. Initial microregion specific control variables include: the percent employment in traded sectors, percent employment that is high school educated, percent employment that is foreign born, percent employment in routine occupations, the average offshorability index, and the percent employment that is female where appropriate (all from the start of the period, $t$).

There are three important identification assumptions: (1) the change in Chinese import exposure in Brazil is correlated with the change in Chinese import exposure in other countries, (2) the change in Chinese export exposure in Brazil is correlated with the change in Chinese export exposure in other countries, and (3) the change in Chinese import and export exposure in other countries are not correlated with local labor market outcomes in Brazil. If these assumptions hold, the instrumental variables isolate the

\textsuperscript{24}Export IV countries include: Chile, Colombia, Mexico, Peru, South Africa, Thailand, Uruguay, and Venezuela.
impact of increased imports from China and increased exports to China on local labor market outcomes in Brazil and are not confounded by internal factors in Brazil. These internal factors include changing attitudes towards females in the labor force and internal supply and demand factors in Brazil due to economic growth.

Dependent variables of interest include: employment growth rates by gender, wage growth rates by gender, the change in the share of female employment, the change in the average female to male wage ratio, and the change in occupation segregation. All dependent variables are split into two categories, traded sector and non-traded sector outcomes, based on whether the industry had positive trade values with China for the sample. For example, microregion employment outcomes of interest include employment growth rates by gender in the traded sector and those in the non-traded sector. All dependent variables measure the change or growth in specific microregion outcomes from 2008 to 2013. Therefore, the change in Chinese import exposure variables and the change in Chinese export exposure variables are also calculated as the five-year change from 2008 to 2013.\textsuperscript{25} The instrumental variables use lagged employment levels from 2004.

To measure occupation segregation I use the index of segregation developed by Duncan and Duncan (1955), which is the most common occupation segregation index. The index is usually interpreted as the percentage of females that would have to change occupations in order for the male and female occupation distributions to equal one another (Blau et al., 2013). The change in the index of occupation segregation is calculated as the change from 2008 to 2013. Negative values for the change in occupation segregation reflect improvements in occupation segregation. The specific equation for occupation segregation, $S_{it}$, is included in the appendix in section 2.7.1.

I further break the change in occupation segregation down into two components: gender composition and occupation composition, following Blau et al. (2013) (who follow Fuchs (1975)). The gender composition component accounts for how occupation

\textsuperscript{25}Autor et al. (2013) use ten-year or seven-year periods, but due to data limitations I use a five-year period.
segregation would have changed if only the gender composition within occupations changed but occupation sizes remained constant. The occupation composition component accounts for how occupation segregation would have changed if only the relative size of occupations changed and the gender composition remained constant. The decomposition identifies whether occupation segregation changes due to changes in the relative proportion of males and females within occupations (such as females entering male dominated occupations) or due to changes in the occupation structure of the economy (such as occupation sizes growing or shrinking). Specific equations for the gender composition, \( G_{it} \), and occupation composition, \( O_{it} \), are included in the appendix in section 2.7.1.

2.5 Data

This project uses two main sources of data: (1) Brazilian labor market data, and (2) trade data for Brazil and other countries. The Brazilian labor market data, the Relação Anual de Informações Sociais (RAIS), is collected annually by the Brazilian Ministry of Labor (MTE). The RAIS data set is a matched employer-employee data set that covers the entire formal labor market in Brazil, which allows researchers to track workers, establishments, and firms across time. All tax-registered businesses are required to submit detailed information on every employee to the MTE on an annual basis to facilitate payment of the 13th salary, a bonus payment made to eligible workers at the end of the year. Workers have great incentive to ensure accurate information is reported to the MTE as eligible employees only receive their annual bonus if their information is filed correctly (Dix-Carneiro & Kovak, 2017a).

I use the RAIS data for the years 2004 to 2013, which provides rich information on each worker, such as age, gender, industry, wage, education, municipal location, occupation, etc., to measure various local labor market outcomes and demographic characteristics for each microregion. The analysis is restricted to full-time (at least 35 hours per week),
working-age individuals (18-64). In the event that an individual employee appears in the data more than once in a given year, I keep the observation with the highest wage. In order to calculate microregion demographic variables, individual worker characteristics are averaged within each microregion for each year, such as the share of female employment in each microregion. Wages are defined as the worker’s monthly wage in Brazilian reals and all wages are converted to 2013 Brazilian reals using the Brazilian CPI.

The trade data for Brazil and the other selected countries comes from the UN Comtrade database. The UN Comtrade database reports national trade data at the product level using the Harmonized Commodity and Coding System (HS) for over 150 countries. I use import data reported at the 6-digit product level for selected countries for the years 2008 to 2013. While data for both import and export flows is available, only import data is used to ensure the data is consistent. For example, to measure the value of exports from Brazil to China, import data for China is used and to measure the value of imports from China to Brazil, import data for Brazil is used.

Table 2.1 shows the value of trade with China and the value of trade with the rest of the world for Brazil and for other selected countries for the years 2004, 2008, and 2013. Panel A shows the value of trade for Brazil and Panel B shows the value of trade for selected other countries. The first and second columns of Table 2.1 show the value of annual imports from and exports to China for the years 2004, 2008 and 2013. From 2008 to 2013, imports from China grew by over 85% for Brazil and other selected countries. Exports to China grew by approximately 180% for Brazil and by 95% for other selected countries from 2008 to 2013. The third and fourth columns of Table 2.1 show the value of annual imports from the rest of the world and exports to the rest of the world for the years

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26 The results are also robust to using 40 hours per week as the definition for full-time employment.
27 CPI data is from The World Bank. Cumulative inflation from 2008 to 2013 in Brazil was approximately 24%.
28 Import data is known to be more accurate than export data because countries usually keep more accurate records of products flowing into the country.
29 Selected other countries for imports (exports) include all countries included in the change in Chinese import (export) exposure per worker in other countries instrumental variable and are listed in footnote 22 (23).
Table 2.1: Value of Trade with China and the Rest of the World for Brazil and Other Selected Countries: 2004-2013

<table>
<thead>
<tr>
<th>Panel A. Brazil</th>
<th>Imports from China (1)</th>
<th>Exports to China (2)</th>
<th>Imports from rest of world (3)</th>
<th>Exports to rest of world (4)</th>
</tr>
</thead>
<tbody>
<tr>
<td>2004</td>
<td>3.7</td>
<td>5.4</td>
<td>59.1</td>
<td>91.2</td>
</tr>
<tr>
<td>2008</td>
<td>20.0</td>
<td>16.5</td>
<td>152.9</td>
<td>181.4</td>
</tr>
<tr>
<td>2013</td>
<td>37.3</td>
<td>46.0</td>
<td>202.4</td>
<td>196.0</td>
</tr>
<tr>
<td>Growth 2004 - 2008</td>
<td>440.2%</td>
<td>203.7%</td>
<td>158.7%</td>
<td>98.9%</td>
</tr>
<tr>
<td>Growth 2008 - 2013</td>
<td>86.1%</td>
<td>178.6%</td>
<td>32.4%</td>
<td>8.0%</td>
</tr>
</tbody>
</table>

Panel B. Selected Other Countries*

<table>
<thead>
<tr>
<th></th>
<th>Imports from China (1)</th>
<th>Exports to China (2)</th>
<th>Imports from rest of world (3)</th>
<th>Exports to rest of world (4)</th>
</tr>
</thead>
<tbody>
<tr>
<td>2004</td>
<td>21.9</td>
<td>18.8</td>
<td>244.1</td>
<td>411.0</td>
</tr>
<tr>
<td>2008</td>
<td>70.1</td>
<td>52.6</td>
<td>524.3</td>
<td>711.4</td>
</tr>
<tr>
<td>2013</td>
<td>131.3</td>
<td>102.7</td>
<td>677.5</td>
<td>876.0</td>
</tr>
<tr>
<td>Growth 2004 - 2008</td>
<td>220.1%</td>
<td>179.8%</td>
<td>114.8%</td>
<td>73.1%</td>
</tr>
<tr>
<td>Growth 2008 - 2013</td>
<td>87.3%</td>
<td>95.2%</td>
<td>29.2%</td>
<td>23.1%</td>
</tr>
</tbody>
</table>

Notes: Trade values calculated using UN Comtrade data and are reported as billions of USD. *Selected other countries for imports (columns 1 and 3) include: Argentina, Chile, Colombia, Indonesia, Peru, South Africa, and Thailand. Selected other countries for exports (columns 2 and 4) include: Chile, Colombia, Mexico, Peru, Thailand, Uruguay, and Venezuela.

2004, 2008, and 2013. Brazil’s imports from the rest of the world grew by approximately 32% while their exports to the rest of the world grew by approximately 8% from 2008-2013. Selected other countries’ imports from the rest of the world grew by approximately 30% and exports to the rest of the world grew by approximately 23% from 2008 to 2013.

For all categories trade with China grew at a much higher rate than trade with the rest of the world. For example, Brazil’s imports from China increased nearly three times more than Brazil’s imports from the rest of the world and Brazil’s exports to China increased over twenty times more than Brazil’s exports to the rest of the world from 2008 to 2013. The pattern is similar for the selected other countries. Selected other countries’ imports from China grew approximately 2.5 times more than imports from the rest of the world and exports to China grew approximately 3 times more than exports to the rest of the world from 2008 to 2013. The fact that Brazil and other countries’ trade with China grew at a much higher rate than their trade with the rest of the world lends support to the
In order to link the UN Comtrade data to the RAIS data for analysis purposes it is necessary to map each product to an industry. Following the literature, I map each 6-digit HS product code to a 4-digit industry code (ISIC; International Standard Industrial Classification of All Economic Activities) using concordances provided by The World Bank’s World Integrated Trade Solution.\textsuperscript{30} The RAIS data also includes detailed industry information for each worker using Brazil’s National Classification of Economic Activities (CNAE) to identify industries. Therefore, it is also necessary to map each ISIC industry to one CNAE industry using concordances provided by the Brazilian Institute of Geography and Statistics (IBGE).\textsuperscript{31} To ensure that each CNAE industry maps to exactly one ISIC industry (and visa versa), I aggregate the CNAE and ISIC industries where necessary.\textsuperscript{32}

The model specifications include controls for each microregion’s initial percent employment high school educated, percent employment foreign born, percent employment in traded sectors, percent employment female (where appropriate), percent employment in routine jobs, and the average offshorability index. Routine occupation data and offshorability index data are from Dorn (2009) and Autor and Dorn (2013), respectively. The routine occupation data and offshorability index data include 330 occupations based on US Census occupation codes. The RAIS data identifies each workers occupation using the Brazilian Occupation Classification (CBO; Classificação Brasileira de Ocupações). Therefore, I also map the Autor and Dorn (2013) occupation codes to Brazilian occupation codes.\textsuperscript{33}

Table 2.2 shows microregion summary statistics for the year 2013. Summary statistics are shown for: (1) microregion workers employed in traded sectors and (2) those employed in non-traded sectors. Both mean and median values are presented. The number of microregions included in each panel remains constant at 558. While the number of

\textsuperscript{30}Concordances are available for download at http://wits.worldbank.org/product_concordance.html.

\textsuperscript{31}http://concla.ibge.gov.br/images/concla/documentacao/CIIUxCNAE.pdf

\textsuperscript{32}Detailed information for the concordances and aggregations are available upon request.

\textsuperscript{33}Occupation concordances are available upon request.
Table 2.2: Microregion Summary Statistics, Traded and Non-traded Sectors (2013)

<table>
<thead>
<tr>
<th>Variable Name</th>
<th>Traded Sectors</th>
<th></th>
<th>Non-Traded Sectors</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>(1)</td>
<td>(2)</td>
<td>(3)</td>
<td>(4)</td>
</tr>
<tr>
<td></td>
<td>mean</td>
<td>median</td>
<td>sd</td>
<td>mean</td>
</tr>
<tr>
<td>Micro Male Employment</td>
<td>13,110</td>
<td>5,367</td>
<td>28,723</td>
<td>35,950</td>
</tr>
<tr>
<td>Micro Female Employment</td>
<td>5,499</td>
<td>1,366</td>
<td>14,068</td>
<td>21,835</td>
</tr>
<tr>
<td>Micro Share Female Employment</td>
<td>23.65</td>
<td>22.14</td>
<td>11.46</td>
<td>35.82</td>
</tr>
<tr>
<td>Micro Average Male Wage</td>
<td>1,482.44</td>
<td>1,351.81</td>
<td>677.86</td>
<td>1,337.87</td>
</tr>
<tr>
<td>Micro Average Female Wage</td>
<td>1,126.66</td>
<td>1,028.26</td>
<td>449.86</td>
<td>1,033.42</td>
</tr>
<tr>
<td>Micro Wage Ratio</td>
<td>78.93</td>
<td>77.03</td>
<td>14.51</td>
<td>78.48</td>
</tr>
<tr>
<td>Micro Occupation Segregation</td>
<td>62.0</td>
<td>61.0</td>
<td>14.0</td>
<td>62.0</td>
</tr>
</tbody>
</table>

Growth/Δ from 2008 to 2013

<table>
<thead>
<tr>
<th>Variable Name</th>
<th>Traded Sectors</th>
<th></th>
<th>Non-Traded Sectors</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>(1)</td>
<td>(2)</td>
<td>(3)</td>
<td>(4)</td>
</tr>
<tr>
<td></td>
<td>mean</td>
<td>median</td>
<td>sd</td>
<td>mean</td>
</tr>
<tr>
<td>Male Employment Growth (%)</td>
<td>-10.26</td>
<td>2.29</td>
<td>59.40</td>
<td>24.63</td>
</tr>
<tr>
<td>Female Employment Growth (%)</td>
<td>-3.00</td>
<td>16.49</td>
<td>70.65</td>
<td>26.61</td>
</tr>
<tr>
<td>Δ Share Female Employment (pp)</td>
<td>2.02</td>
<td>1.98</td>
<td>6.10</td>
<td>1.28</td>
</tr>
<tr>
<td>Male Wage Growth (%)</td>
<td>22.51</td>
<td>24.29</td>
<td>24.61</td>
<td>19.94</td>
</tr>
<tr>
<td>Female Wage Growth (%)</td>
<td>22.04</td>
<td>24.41</td>
<td>30.80</td>
<td>21.85</td>
</tr>
<tr>
<td>Δ Average Wage Ratio (pp)</td>
<td>-0.31</td>
<td>0.04</td>
<td>13.10</td>
<td>1.79</td>
</tr>
<tr>
<td>Δ Occupation Segregation (pp)</td>
<td>-1.09</td>
<td>-0.92</td>
<td>10.74</td>
<td>1.83</td>
</tr>
</tbody>
</table>

Counts

<table>
<thead>
<tr>
<th>Variable Name</th>
<th>Traded Sectors</th>
<th></th>
<th>Non-Traded Sectors</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Microregion Counts (n = 558)</td>
<td></td>
<td>558</td>
<td>558</td>
<td></td>
</tr>
<tr>
<td>Industry Counts (n = 294)</td>
<td></td>
<td>147</td>
<td>147</td>
<td></td>
</tr>
</tbody>
</table>

Notes: Microregion summary statistics for full-time, working age formal sector workers by for the year 2013 broken down by traded sectors and non-traded sectors. The number of industries included in calculating various labor market outcomes changes by trade category, but the number of microregions remains constant across all industries and various trade categories.

Industries appears to remain constant, there are 147 industries with positive trade values in the traded sector and a different 147 industries with zero trade values in the non-traded sector. Table 2.2 shows that average microregion male employment in 2013 is over 13,000 in traded sectors and approximately 36,000 in non-traded sectors. Mean and median male employment is consistently larger than female employment and females are most represented in the non-traded sector. Female wages are approximately 79% of male wages in both the traded and non-traded sector. Occupation segregation is high on average at 62% for both the traded and non-traded sectors. This indicates that 62% of females need to switch occupations in order for the female occupation distribution and the male...
occupation distribution to be equal.\textsuperscript{34}

For the five-year growth rates from 2008 to 2013, average male and female employment growth in the traded sector is negative, but the medians are positive. Employment gains in the non-traded sector are relatively large, 24\% for males and 26\% for females. The share of female employment increased by one to two percentage points in both sectors. Male and females also experienced relatively large wage gains from 2008 to 2013 in both sectors. Male and female wage gains, approximately 22\% on average in the traded sector and 20\% to 21\% in the non-traded sector, are both high over the sample period. The relatively high wage gains are due to the fact that Brazil indexes their wages to the minimum wage and the minimum wage increased by almost 40\% over the sample. However, female wages grew by a slightly higher amount than male wages in the non-traded sector, which translates to an increase in the average wage ratio. The average wage ratio declined on average in traded sectors, but the median change is positive. The numbers for the change in occupation segregation are similar. Traded sector occupation segregation declined on average, while it increased in the non-traded sector.

The summary statistics for Brazil’s two trade exposure variables, the change in Chinese import exposure per worker in Brazil and the change in Chinese export exposure per worker in Brazil, and the two instrumental variables are shown in Table 2.3. In addition to the mean value and standard deviation, the minimum, maximum, 25th, 50th, and 75th percentiles are also shown to illustrate the variation in the trade exposure variables across microregions. For example, the change in Chinese import exposure per worker in Brazil is $270 on average, but the 25th percentile is only $85 while the 75th percentile is $360. The variation in exports is even larger. The average change in Chinese export exposure per worker in Brazil is approximately $1,350, the 25th percentile is $110 while the 75th percentile is $1,370. The variation for both instrumental variables is also similar.\textsuperscript{35} Trade

\textsuperscript{34}Summary statistics for microregion start of period controls are included in the appendix in Table 2.12. \textsuperscript{35}The values for the instrumental variables are larger than the values for the Brazil specific variables because they aggregate trade values for eight countries. The Brazil specific variables only include trade values for Brazil.
Table 2.3: Summary Statistics for Trade Exposure Measures, 2008-2013

<table>
<thead>
<tr>
<th></th>
<th>(1) p25</th>
<th>(2) p50</th>
<th>(3) p75</th>
<th>(4) mean</th>
<th>(5) sd</th>
<th>(6) min</th>
<th>(7) max</th>
</tr>
</thead>
<tbody>
<tr>
<td>Δ Imports from China to Brazil per worker (IPW\textsubscript{bit})</td>
<td>85</td>
<td>183</td>
<td>357</td>
<td>269</td>
<td>424</td>
<td>-3,740</td>
<td>3,335</td>
</tr>
<tr>
<td>Δ Imports from China to other countries per worker (IPW\textsubscript{oit})</td>
<td>435</td>
<td>913</td>
<td>1,711</td>
<td>1,567</td>
<td>3,022</td>
<td>-1,185</td>
<td>21,987</td>
</tr>
<tr>
<td>Δ Exports to China from Brazil per worker (EPW\textsubscript{bit})</td>
<td>110</td>
<td>381</td>
<td>1,362</td>
<td>1,349</td>
<td>3,464</td>
<td>-2,774</td>
<td>53,481</td>
</tr>
<tr>
<td>Δ Exports to China from other countries per worker (EPW\textsubscript{oit})</td>
<td>333</td>
<td>946</td>
<td>2,401</td>
<td>4,071</td>
<td>16,325</td>
<td>-345</td>
<td>78,072</td>
</tr>
</tbody>
</table>

Notes: Calculated using UN Comtrade data for the years 2008 and 2013 and RAIS data for the years 2004-2013. p# indicates the #th percentile. Import IV countries include: Argentina, Chile, Colombia, Indonesia, Peru, South Africa, Thailand, and Uruguay. Export IV countries include: Chile, Colombia, Mexico, Peru, South Africa, Thailand, Uruguay, and Venezuela.

values for all industries are included when calculating the trade exposure measures.

2.6 Results

Before summarizing the results from the second stage analyses, it is worthwhile to first examine the predictive power of the instrumental variables. Figure 2.2 plots the change in predicted trade exposure per worker in Brazil measures against the change in actual trade exposure per worker in Brazil for the year 2013.\textsuperscript{36} Panel A plots change in Chinese import exposure values and Panel B plots change in Chinese export exposure values. The coefficient of 0.97 in Panel A indicates that a $100 predicted increase in the change in import exposure per worker in Brazil corresponds with a $97 actual increase in the change in import exposure per worker in Brazil.\textsuperscript{37} Similarly, the coefficient of 0.81 in Panel B

\textsuperscript{36}The change in predicted trade exposure per worker in Brazil variables are calculated using regressions of the change in import (export) exposure per worker in Brazil on the change in import exposure per worker in other countries and the change in export exposure per worker in other countries, weighted by the start of period microregion employment.

\textsuperscript{37}The coefficient 0.97 (0.81) is calculated by regressing the change in actual import (export) exposure per worker on the change in predicted import (export) exposure per worker in Brazil.
indicates that a $100 predicted increase in the change in export exposure per worker corresponds with an $81 actual increase in the change in export exposure per worker.

To further investigate the predictive power of the instrumental variables, Table 2.4 shows the first stage estimates from the 2SLS models. Only the variables of interest, the two instrumental variables, are included for the sake of space. The table shows that the instrumental variables are significant and of expected sign. Imports in other countries predict imports in Brazil and exports in other countries predict exports in Brazil. The coefficient of 0.180 for imports in column (1) indicates that a one dollar increase in the change in Chinese import exposure in other countries predicts an increase in the change in Chinese import exposure in Brazil of 18 cents. While this seems small in magnitude, the average change in Chinese import exposure for other countries is approximately $1,200, which corresponds to a predicted change in Chinese import exposure per worker in Brazil of $216. This is relatively close to the average change in Chinese import exposure in Brazil, $270. The coefficient of 0.185 for exports in column (2) indicates that a one dollar increase in the change in Chinese export exposure per worker in other countries predicts a change in Chinese export exposure per worker in Brazil of 18.5 cents. The average change in Chinese export exposure in other countries is approximately $3,000, which corresponds to a predicted change in Chinese export exposure in Brazil of $540 (the mean increase is $1,350). Figure 2.2 and Table 2.4 together provide strong evidence that the instrumental variables have high predictive power.

Table 2.5 analyzes microregion employment outcomes for the traded and non-traded sector. Only estimates for the two independent variables of interest, the change in Chinese import and export exposure per worker in Brazil, are presented for the sake of space. All specifications include controls for each microregion’s initial percent employment high school educated, foreign born, in routine jobs, in traded sectors, initial average offshorability index, region controls, and a constant. The control variables capture different demographic characteristics across microregions that are also likely to affect labor market outcomes.
Figure 2.2: 2SLS First Stage Estimates, 2013

(a) Import Exposure per Worker in Brazil

![Graph showing the relationship between change in predicted import exposure per worker and change in import exposure per worker in Brazil.]

(b) Export Exposure per Worker in Brazil

![Graph showing the relationship between change in predicted export exposure per worker and change in export exposure per worker in Brazil.]

Notes: N=558. RAIS data, 2004-2013 and UN Comtrade data 2008-2013. Change in predicted import (export) exposure per worker is calculated from the regression of the change in import (export) exposure per worker in Brazil on the change in import and export exposure per worker in other countries, weighted by the initial (2008) microregion share of national employment. The coefficient captures the OLS relationship between the predicted import (export) exposure per worker and the actual value of import (export) exposure per worker.
Table 2.4: Trade with China, First Stage Estimates, 2008-2013

<table>
<thead>
<tr>
<th></th>
<th>( \Delta IPW_{bit} )</th>
<th>( \Delta EPW_{bit} )</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>(1)</td>
<td>(2)</td>
</tr>
<tr>
<td>( \Delta ) Imports from China to other countries per worker</td>
<td>0.180*** (0.020)</td>
<td>-0.012 (0.045)</td>
</tr>
<tr>
<td>( \Delta ) Exports to China from other countries per worker</td>
<td>0.000 (0.003)</td>
<td>0.185** (0.089)</td>
</tr>
<tr>
<td>N</td>
<td>557</td>
<td>557</td>
</tr>
<tr>
<td>( R^2 )</td>
<td>0.697</td>
<td>0.412</td>
</tr>
</tbody>
</table>

Notes: Change in import and export exposure variables are calculated as the change from 2008 to 2013. All models include a constant, region controls, controls for the initial microregion percent employment high school educated, foreign born, in routine jobs, in traded sectors, and initial average offshorability index. Standard errors in parentheses are clustered at the state level and models are weighted by 2008 microregion employment shares. * p < 0.10, ** p < 0.05, *** p < 0.01.

The results in Panel A indicate that the change in Chinese export exposure is positively associated with male employment growth, female employment growth, and the change in the share of female employment in the traded sector. The coefficient of 0.10 in column (1) of Panel A indicates that a $1 increase in the change in export exposure corresponds with an increase in male employment growth of 0.01 percentage points. For the average microregion, this translates to male employment growth of 13.5 percentage points, or 1,750 jobs. The coefficient for female employment growth in column (2) is slightly larger at 0.015, which corresponds to average female employment growth of 20 percentage points, or 1,100 jobs, and an increase in the share of female employment of 1.35 percentage points.

The increase in Chinese import exposure is also positively associated with the share of female employment. For the average microregion, this corresponds to an increase of 0.27 percentage points in the share of female employment. For workers employed in the traded sector, increased trade with China improves women’s relative local employment position in Brazil.

Panel B of Table 2.5 shows the microregion employment results for the non-traded

---

38 Average microregion change in Chinese export exposure is approximately $1,350, which when multiplied by 0.01 equals 13.5.
Table 2.5: Trade with China and Microregion Employment Outcomes, 2008-2013

<table>
<thead>
<tr>
<th></th>
<th>Male Emp. Growth (1)</th>
<th>Female Emp. Growth (2)</th>
<th>Δ Share Female Emp. (3)</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Panel A. Traded Sector Employment Outcomes</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Δ Imports from China to Brazil per worker</td>
<td>0.012</td>
<td>0.024</td>
<td>0.001**</td>
</tr>
<tr>
<td></td>
<td>(0.016)</td>
<td>(0.020)</td>
<td>(0.000)</td>
</tr>
<tr>
<td>Δ Exports to China from Brazil per worker</td>
<td>0.010*</td>
<td>0.015*</td>
<td>0.001*</td>
</tr>
<tr>
<td></td>
<td>(0.006)</td>
<td>(0.008)</td>
<td>(0.000)</td>
</tr>
<tr>
<td>N</td>
<td>557</td>
<td>556</td>
<td>557</td>
</tr>
<tr>
<td>$R^2$</td>
<td>0.553</td>
<td>0.577</td>
<td>0.411</td>
</tr>
<tr>
<td><strong>Panel B. Non-traded Sector Employment Outcomes</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Δ Imports from China to Brazil per worker</td>
<td>0.002</td>
<td>0.011</td>
<td>0.001**</td>
</tr>
<tr>
<td></td>
<td>(0.006)</td>
<td>(0.009)</td>
<td>(0.001)</td>
</tr>
<tr>
<td>Δ Exports to China from Brazil per worker</td>
<td>0.004</td>
<td>0.008*</td>
<td>0.001**</td>
</tr>
<tr>
<td></td>
<td>(0.002)</td>
<td>(0.004)</td>
<td>(0.000)</td>
</tr>
<tr>
<td>N</td>
<td>558</td>
<td>558</td>
<td>558</td>
</tr>
<tr>
<td>$R^2$</td>
<td>0.562</td>
<td>0.595</td>
<td>0.382</td>
</tr>
</tbody>
</table>

Notes: Microregion employment growth rates and change in employment variables are calculated from 2008 to 2013. All models include a constant, region controls, controls for the initial microregion percent employment high school educated, foreign born, in routine jobs, in traded sectors, and initial average offshorability index. First stage estimates for all panels are identical to those in Table 2.4 and are therefore not included. Standard errors in parentheses are clustered at the state level and models are weighted by 2008 microregion employment shares. * p<0.10, ** p<0.05, *** p<0.01.

sector. The results continue to support the notion that trade is positively associated with female employment. For example, the coefficient of 0.008 in column (2) indicates that the average microregion experienced female employment growth in the non-traded sector of 10.8 percentage points, or 2,350 jobs. Without a simultaneous increase in male employment growth, this translates to an increase in the share of female employment of 1.35 percentage points. The change in Chinese import exposure is also positively related to the change in the share of female employment. The average microregion experienced an increase in the share of female employment of 0.27 percentage points in response to increased Chinese import exposure. Females are more likely to gain employment in the non-traded sector in response to increased trade with China.
There are also significant differences in employment gains from trade with China across microregions due to the variation in the change in Chinese trade exposure variables. For example, a microregion at the 75th percentile of the change in Chinese export exposure experienced male and female employment gains in the traded sector approximately 12.5 and 18.75 percentage points higher, respectively, than a microregion at the 25th percentile. Female employment gains in the non-traded sector for a microregion at the 75th percentile were approximately 10 percentage points higher than a microregion at the 25th percentile. Females’ relative employment position improves in both the traded and non-traded sector in response to both imports from China and exports to China. It is also important to point out that females’ relative employment gains do not come at the expense of declining male employment growth.

Table 2.6 shows the results for the change in Chinese trade exposure and microregion wage outcomes for the traded sector (Panel A) and the non-traded sector (Panel B). The results in Panel A indicate that the change in Chinese export exposure is positively associated with female wage growth in the traded sector. For the average microregion, the coefficient of 0.0012 in column (2) corresponds to female wage growth of 1.62 percentage points. This only translates to approximately 20 Brazilian reals per month though. The difference in female wage growth for a microregion at the 75th and 25th percentile of export exposure is 1.5 percentage points, which corresponds to wages approximately 20 Brazilian reals higher per month. The change in Chinese trade exposure variables do not have a significant relationship with male wage growth or the change in the average wage ratio. Panel B also shows that increased Chinese trade exposure continues to positively affect female wages in the non-traded sector. However, for the non-traded sector, the change in Chinese import exposure is positively related to female wage growth. The coefficient of 0.0029 in column (2) corresponds to average female wage growth of 0.78 percentage points in the non-traded sector. However, this only translates to a wage increase of less than 10 Brazilian reals per month. While trade is positively impacting female wage
growth, the gains are not large in nature, but the gains do reflect positive real wage growth.

The results in Table 2.5 and Table 2.6 indicate that increased trade with China has some spillover effects into the non-traded sector. Increased Chinese export exposure could have spillover effects into the non-traded sector for two reasons. As employment grows in the traded sector, those workers now have a higher demand for non-traded goods, likely services. The second explanation is that non-traded goods and services could be complementary to the production processes of traded goods. For example, this would be true if the production of traded goods also requires advertising or financial services. However, the results for the non-traded sector contrast with the predictions of the model developed by Autor et al. (2013). The model predicts that increased imports should
Table 2.7: Trade with China and Microregion Occupation Segregation, 2008-2013

<table>
<thead>
<tr>
<th></th>
<th>( \Delta ) Occupation Segregation</th>
<th>Gender Composition</th>
<th>Occupation Composition</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>(1)</td>
<td>(2)</td>
<td>(3)</td>
</tr>
<tr>
<td><strong>Panel A. Traded Sector Occupation Segregation</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>( \Delta ) Imports from China to Brazil per worker</td>
<td>-0.002***</td>
<td>-0.036*</td>
<td>0.034*</td>
</tr>
<tr>
<td></td>
<td>(0.001)</td>
<td>(0.021)</td>
<td>(0.020)</td>
</tr>
<tr>
<td>( \Delta ) Exports to China from Brazil per worker</td>
<td>-0.001</td>
<td>-0.016*</td>
<td>0.015*</td>
</tr>
<tr>
<td></td>
<td>(0.000)</td>
<td>(0.008)</td>
<td>(0.008)</td>
</tr>
<tr>
<td>N</td>
<td>558</td>
<td>558</td>
<td>558</td>
</tr>
<tr>
<td>( R^2 )</td>
<td>0.145</td>
<td>0.042</td>
<td>0.041</td>
</tr>
</tbody>
</table>

| **Panel B. Non-traded Sector Occupation Segregation** |                                     |                    |                        |
| \( \Delta \) Imports from China to Brazil per worker | -0.000                            | -3.807             | 3.806                  |
|                        | (0.000)                             | (2.320)            | (2.320)                |
| \( \Delta \) Exports to China from Brazil per worker | -0.001**                          | -1.295             | 1.294                  |
|                        | (0.000)                             | (1.194)            | (1.194)                |
| N                      | 558                                 | 558                | 558                    |
| \( R^2 \)              | 0.242                               | 0.028              | 0.028                  |

*Notes:* Microregion occupation segregation and its components are calculated from 2008 to 2013. All models include a constant, region controls, controls for the initial microregion percent employment high school educated, female, foreign born, in routine jobs, in traded sectors, and initial average offshorability index. First stage estimates for all panels are identical to those in Table 2.4 and are therefore not included. Standard errors in parentheses are clustered at the state level and models are weighted by 2008 microregion employment shares. * \( p<0.10 \), ** \( p<0.05 \), *** \( p<0.01 \)

increase employment in the non-traded sector while increased exports should decrease employment in the non-traded sector. The results indicate that increased Chinese export exposure increased employment and wages in the non-traded sector, but the gains were exclusive to females. Increased Chinese import exposure did not significantly affect male or female employment, but they did increase the share of female employment and female wages in the non-traded sector. The results support the mechanism of skill-biased technical change in favor of female employment and labor segregation and reallocation thus far. Exports are complementary to female employment and females are more likely to gain employment in the non-traded sector.

To further explore the role of labor segregation, I also analyze the relationship
between the change in Chinese trade exposure and the change in occupation segregation in Brazilian microregions. Trade has the potential to impact occupation distributions and occupation segregation through two channels: (1) increased trade causes employment shifts which can lead workers to reallocate to different occupations, and (2) increased trade causes changes in the relative size of certain occupations that are more or less susceptible to the impacts of trade. Table 2.7 shows the results for the change in Chinese trade exposure variables and occupation segregation and its components for the traded and non-traded sector. The change in Chinese import exposure is negatively associated with the change in occupation segregation in the traded sector (column (1) panel A); however, the change in Chinese export exposure is negatively associated with the change in occupation segregation in the non-traded sector (column (1) panel B). For the average microregion, imports decrease occupation segregation by approximately 0.5 percentage points in the traded sector and exports decrease occupation segregation by approximately 1.35 percentage points. While the decreases are not extremely large, the decreases are economically significant since occupation segregation is considered the most persistent reason for continued gender gaps. The fact that both Chinese import and Chinese export exposure negatively impact the gender composition in the traded sector, where females are least represented, further supports the economic significance. Trade with China changed the relative proportion of males and females within occupations in the traded sector, decreasing the level of occupation segregation, which further benefits females in the labor market.

Previous research has found some evidence that the impacts of trade are mostly concentrated in low-skilled employment. Gaddis and Pieters’ (2017) found that negative employment outcomes in response to Brazil’s trade liberalization episode were extremely concentrated in low-skilled employment. Therefore, I further break down the analysis of employment and wage outcomes by skill to determine if the China trade shock has differential effects by gender and by skill level. I use education as a proxy for skill, defining a high-skilled worker as a worker with a high school diploma and a low-skilled worker as
Table 2.8: Trade with China and Microregion Employment Outcomes by Skill, 2008-2013

<table>
<thead>
<tr>
<th></th>
<th>High School Diploma+</th>
<th>No High School Diploma</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Panel A. Traded Sector Employment Outcomes</td>
<td></td>
<td></td>
</tr>
<tr>
<td>ΔIPW&lt;sub&gt;bit&lt;/sub&gt;</td>
<td>0.0121 (0.0286)</td>
<td>0.0155 (0.0191)</td>
</tr>
<tr>
<td>ΔEPW&lt;sub&gt;bit&lt;/sub&gt;</td>
<td>0.0166* (0.0093)</td>
<td>0.0134* (0.0071)</td>
</tr>
<tr>
<td>N</td>
<td>556</td>
<td>555</td>
</tr>
<tr>
<td>R&lt;sup&gt;2&lt;/sup&gt;</td>
<td>0.613</td>
<td>0.601</td>
</tr>
</tbody>
</table>

Panel B. Non-traded Sector Employment Outcomes

<table>
<thead>
<tr>
<th></th>
<th>High School Diploma+</th>
<th>No High School Diploma</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>ΔIPW&lt;sub&gt;bit&lt;/sub&gt;</td>
<td>0.0106 (0.0085)</td>
<td>0.0114 (0.0080)</td>
</tr>
<tr>
<td>ΔEPW&lt;sub&gt;bit&lt;/sub&gt;</td>
<td>0.0078* (0.0044)</td>
<td>0.0077* (0.0041)</td>
</tr>
<tr>
<td>N</td>
<td>558</td>
<td>558</td>
</tr>
<tr>
<td>R&lt;sup&gt;2&lt;/sup&gt;</td>
<td>0.625</td>
<td>0.617</td>
</tr>
</tbody>
</table>

Notes: Microregion employment growth rates and change in employment variables are calculated from 2008 to 2013. All models include a constant, region controls, controls for the initial microregion percent employment high school educated, foreign born, in routine jobs, in traded sectors, and initial average offshorability index. First stage estimates for all panels are identical to those in Table 2.4 and are therefore not included. Standard errors in parentheses are clustered at the state level and models are weighted by 2008 microregion employment shares. * p<0.10, ** p<0.05, *** p<0.01

those without a high-school diploma. Autor et al. (2013) also use education as a proxy for skill, but define a high-skilled worker as one with a college degree and a low-skilled worker as one without a college degree. However, college degrees are much less common in Brazil than the US, so a high school degree is a more realistic representation of skill in Brazil. On average, females are slightly less educated than males in Brazil. Therefore, if trade effects are concentrated in low-skilled employment, they could impact females more than males.

Table 2.8 shows the results for microregion employment outcomes by education for the traded sector in Panel A and the non-traded sector in Panel B. The first three columns show the results for high-skilled employment, workers with at least a high school degree,
and columns (4) through (6) show the results for low-skilled employment, workers without a high school degree. Panel A indicates that positive male employment growth in response to increased Chinese export exposure is concentrated in high-skilled male employment. The gains for female employment in the traded sector in response to exports are split between high-skilled and low-skilled female employment, but the increase in the share of female employment is concentrated in high-skilled female employment. Increased Chinese import exposure also has some positive employment effects for males and females in low-skilled traded sector employment. However, the change in Chinese import exposure did not have any significant effects on aggregate male or female employment growth in the traded sector in Table 2.5. The results in Panel B for the non-traded sector are similar. In response to increased Chinese export exposure, male employment gains are concentrated in high-skilled non-traded employment while female employment gains are split between high-skilled and low-skilled non-traded employment. Further, the increase in the share of female employment in the non-traded sector is concentrated in high-skilled female employment.

Table 2.9 shows the results for microregion wage outcomes by gender and skill for the traded sector, Panel A, and the non-traded sector, Panel B. Increased import exposure has a negative relationship with both low-skilled male and female wage growth. These results are in line with Autor et al.’s (2013) model predictions, but imports do not have a negative relationship with wage growth in Table 2.6. Since the decrease is slightly larger for males, this translates to a false improvement in the average wage ratio for low-skilled workers. Panel B shows that the positive wage growth in non-traded sectors in response to increased Chinese import exposure is concentrated in high-skilled female employment. Wage growth for high-skilled males is positively related to the change in Chinese export exposure, but aggregate male wage growth did not have a significant relationship with exports in Table 2.6.

While the wage results are different than the employment results, one clear pattern emerges. Imports from China mostly affect low-skilled workers while exports to China
Table 2.9: Trade with China and Microregion Wage Outcomes by Skill, 2008-2013

<table>
<thead>
<tr>
<th></th>
<th>High School Diploma+</th>
<th>No High School Diploma</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Male (1)</td>
<td>Female (2)</td>
</tr>
<tr>
<td>Wage Growth</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Panel A. Traded Sector Wage Outcomes</td>
<td></td>
<td></td>
</tr>
<tr>
<td>ΔIPW&lt;sub&gt;bit&lt;/sub&gt;</td>
<td>-0.0034</td>
<td>-0.0015</td>
</tr>
<tr>
<td></td>
<td>(0.0039)</td>
<td>(0.0037)</td>
</tr>
<tr>
<td>ΔEPW&lt;sub&gt;bit&lt;/sub&gt;</td>
<td>0.0015</td>
<td>0.0015</td>
</tr>
<tr>
<td></td>
<td>(0.0011)</td>
<td>(0.0011)</td>
</tr>
<tr>
<td>N</td>
<td>556</td>
<td>553</td>
</tr>
<tr>
<td>R&lt;sup&gt;2&lt;/sup&gt;</td>
<td>0.286</td>
<td>0.329</td>
</tr>
<tr>
<td>Panel B. Non-traded Sector Wage Outcomes</td>
<td></td>
<td></td>
</tr>
<tr>
<td>ΔIPW&lt;sub&gt;bit&lt;/sub&gt;</td>
<td>0.0024</td>
<td>0.0034**</td>
</tr>
<tr>
<td></td>
<td>(0.0019)</td>
<td>(0.0014)</td>
</tr>
<tr>
<td>ΔEPW&lt;sub&gt;bit&lt;/sub&gt;</td>
<td>0.0021*</td>
<td>0.0018</td>
</tr>
<tr>
<td></td>
<td>(0.0012)</td>
<td>(0.0012)</td>
</tr>
<tr>
<td>N</td>
<td>558</td>
<td>558</td>
</tr>
<tr>
<td>R&lt;sup&gt;2&lt;/sup&gt;</td>
<td>0.504</td>
<td>0.600</td>
</tr>
</tbody>
</table>

Notes: Microregion wage growth rates and change in wage variables are calculated from 2008 to 2013. All models include a constant, region controls, controls for the initial microregion percent employment high school educated, female, foreign born, in routine jobs, in traded sectors, and initial average offshorability index. First stage estimates for all panels are identical to those in Table 2.4 and are therefore not included. Standard errors in parentheses are clustered at the state level and models are weighted by 2008 microregion employment shares. * p<0.10, ** p<0.05, *** p<0.01

mostly affect high-skilled workers. This is true for both traded sector and non-traded sector employment. In regards to employment growth, high-skilled males benefit more than low-skilled males while low- and high-skilled females both benefit from increased Chinese export exposure. Exports have skill-biased employment gains for high-skilled workers, while imports are associated with gains in low-skilled employment. If trade induces technology upgrades, this could lead to more automated tasks which become suitable for male and female employment (rather than the stereotypical male employee in blue collar jobs). These technological upgrades are most likely to occur in the manufacturing sector, which are also most impacted by increased Chinese import exposure. This also translates
into declining wage growth for low-skilled workers in response to increased Chinese import exposure. However, trade with China in general seems to provide females, both low- and high-skilled, with more employment opportunities. Of equal importance, though, is the fact that trade with China is not simultaneously harming male employment and wage outcomes.

2.7 Conclusion

Brazil is one of many countries that integrated into the world economy, contributing to the continued rise of globalization and international trade. While the country’s trade values have consistently increased since liberalizing their trade policies in the early 1990’s, the rate of increase became much larger in the early 2000’s. This corresponds to China’s accession to the WTO in 2001. Combined with their transition from a central planning to a market-oriented economy, China quickly came to dominate certain world trade markets. The country’s rise, known as the “China trade shock,” led to the emergence of an area of literature specifically focused on the economic impacts of China’s rise. This paper contributes to that literature by examining the impact of increased imports from and exports to China on gender-specific local labor market outcomes in Brazil. The negative effects of increased reliance on Chinese imports is well documented (see Autor et al. (2013), Mion and Zhu (2013), and Iacovone et al. (2013)). This paper determines a channel through which the China trade shock can have positive effects via improving females’ relative local labor market position. The analysis combines UN Comtrade data with the RAIS data, a matched employer-employee data set for the formal labor market in Brazil, to determine the effects of the China trade shock on gender-specific employment, wage, and occupation segregation outcomes in Brazilian microregions.

Overall, the results strongly support the notion that the China trade shock has positive local labor market effects for females. Of equal importance is that females’ relative labor market gains are due to improvements in females’ local labor market outcomes rather than declining male outcomes. Exports have a complementary relationship with female
employment. Increased Chinese export exposure is positively associated with female employment growth and the share of female employment in both the traded and the non-traded sector. Exports also have a positive relationship with female wage growth, but this effect is only seen in the traded sector. Chinese import exposure also has some positive effects on female labor market outcomes in Brazil. Increased Chinese imports are positively related to the share of female employment in both the traded and non-traded sector and female wage growth in the non-traded sector.

When the analysis is broken down by skill, male employment gains from increased Chinese export exposure are concentrated in high-skilled male employment. However, both low- and high-skilled females experience positive employment growth in response to increased Chinese export exposure. While increased imports decrease male and female wage growth in the traded sector, this is likely due to low-skilled employment gains for both males and females in response to increased imports. As more low-skilled workers gain employment, average wage growth declines. Low-skilled males experience slightly larger wage declines, which is in line with Gaddis and Pieters’ (2017) results. Thus, trade with China is creating employment opportunities for both low-skilled and high-skilled females.

The results clearly indicate that the China trade shock improves females’ relative local labor market position in Brazil. However, improvements are not attributed to declining labor market discrimination. This contrasts with Black and Brainerd’s (2004) results for the US, but is in line with Benguria and Ederington’s (2017) results for Brazil. The results support the mechanisms of skill-biased technical change and labor market segregation and reallocation. One potential explanation is that as trade induces technological upgrades females become more suitable for traditionally male, blue-collar occupations. This result is in line with the findings of Juhn et al. (2014) and explains the positive relationship between Chinese export exposure and female employment growth and the share of female employment in the traded sector. Additionally, trade with China also has clear spillover effects into the non-traded sector, which continue to benefit female
employment growth and the share of female employment. This could be due to females being most represented in the non-traded sector and therefore are more likely to gain employment in the non-traded sector. Last, trade with China also decreases occupation segregation in both the traded and the non-traded sector. This further lends support to the labor segregation and reallocation mechanism. As females gain employment in response to increased trade with China, they are entering traditionally male-dominated occupations (or visa versa), which breaks down occupation segregation barriers.

When considering various trade policies and trade relationships, it is important for policy makers to consider both the consequences of increased import competition and the benefits of increased access to export markets. While trade is often considered a mechanism for a country to create continuous economic growth, the results suggest that trade can also improve females’ relative local labor market position without harming male outcomes. This contrasts with Gaddis and Pieters’ (2017) results, which indicate that females’ relative labor market position did not improve in response to Brazil’s trade liberalization. This further indicates why it is important to include both imports and exports in the analysis when studying the effects of trade between two countries, particularly those with a relatively balanced trade relationship. The results provide an additional channel through which the China trade shock can have positive economic benefits. However, it is important to note that the results only apply to the formal sector in Brazil. Given that the informal sector is extremely large in Brazil, future research should determine the effects of the China trade shock on informal employment outcomes and transitions from formal to informal employment (or visa versa).

2.8 Appendix

2.8.1 Supplementary Equations

Following Duncan and Duncan (1955), occupation segregation for microregion \( i \) in year \( t \) is computed as follows:
\[ S_{it} = (0.5) \sum_n |m_{nit} - f_{nit}|, \]  

(2.8)

where \( m_{nit} \) is the proportion of all employed males who are employed in occupation \( n \) in microregion \( i \) in year \( t \) and \( f_{nit} \) is the proportion of all employed females who are employed in occupation \( n \) in microregion \( i \) in year \( t \). A value of zero indicates that occupations are fully integrated and a value of 100 indicates absolute segregation.

The gender composition effect, \( G_{it} \), and the occupation composition effect, \( O_{it} \), are calculated as follows:

\[ G_{it} = (0.5) \sum_n \left| \frac{q_{nit} T_{ni1}}{\sum_n q_{nit} T_{ni1}} - \frac{p_{nit} T_{ni1}}{\sum_n p_{nit} T_{ni1}} \right| - S_{i1}, \]  

(2.9)

\[ O_{it} = S_{i2} - (0.5) \sum_n \left| \frac{q_{nit} T_{ni1}}{\sum_n q_{nit} T_{ni1}} - \frac{p_{nit} T_{ni1}}{\sum_n p_{nit} T_{ni1}} \right|, \]  

(2.10)

where \( q_{nit} \) is the percentage of males in occupation \( n \) in microregion \( i \) in year \( t \) and \( p_{nit} \) is the percentage of females in occupation \( n \) in microregion \( i \) in year \( t \). \( T_{nit} \) is the total number of men and women in occupation \( n \) in microregion \( i \) in year \( t \). \( z \) also represents occupations.
### 2.8.2 Supplementary Tables and Figures

#### Table 2.10: Industry Shares of Total Imports from China (Largest 20), 2013

<table>
<thead>
<tr>
<th>ISIC3 Code</th>
<th>ISIC3 Description</th>
<th>Share of Imports</th>
</tr>
</thead>
<tbody>
<tr>
<td>3000</td>
<td>Manufacture of office, accounting and computing machinery</td>
<td>9.8%</td>
</tr>
<tr>
<td>3230</td>
<td>Manufacture of television and radio receivers, sound or video recording or reproducing apparatus, and associated goods</td>
<td>7.1%</td>
</tr>
<tr>
<td>2411</td>
<td>Manufacture of basic chemicals, except fertilizers and nitrogen compounds</td>
<td>5.7%</td>
</tr>
<tr>
<td>2914</td>
<td>Manufacture of ovens, furnaces and furnace burners</td>
<td>4.3%</td>
</tr>
<tr>
<td>1890*</td>
<td>Manufacture of wearing apparel, articles of fur, and dyeing and dressing of fur</td>
<td>3.7%</td>
</tr>
<tr>
<td>3210</td>
<td>Manufacture of electronic valves and tubes and other electronic components</td>
<td>3.6%</td>
</tr>
<tr>
<td>2710</td>
<td>Manufacture of basic iron and steel</td>
<td>3.4%</td>
</tr>
<tr>
<td>3110</td>
<td>Manufacture of electric motors, generators and transformers</td>
<td>2.7%</td>
</tr>
<tr>
<td>1711</td>
<td>Preparation and spinning of textile fibres; weaving of textiles</td>
<td>2.6%</td>
</tr>
<tr>
<td>2919</td>
<td>Manufacture of other general purpose machinery</td>
<td>2.5%</td>
</tr>
<tr>
<td>3190</td>
<td>Manufacture of other electrical equipment n.e.c.</td>
<td>2.4%</td>
</tr>
<tr>
<td>2912</td>
<td>Manufacture of pumps, compressors, taps and valves</td>
<td>2.0%</td>
</tr>
<tr>
<td>2899</td>
<td>Manufacture of other fabricated metal products n.e.c.</td>
<td>2.0%</td>
</tr>
<tr>
<td>2930</td>
<td>Manufacture of domestic appliances n.e.c.</td>
<td>1.9%</td>
</tr>
<tr>
<td>2423</td>
<td>Manufacture of pharmaceuticals, medicinal chemicals and botanical products</td>
<td>1.9%</td>
</tr>
<tr>
<td>2520</td>
<td>Manufacture of plastics products</td>
<td>1.8%</td>
</tr>
<tr>
<td>2915</td>
<td>Manufacture of lifting and handling equipment</td>
<td>1.6%</td>
</tr>
<tr>
<td>3220</td>
<td>Manufacture of television and radio transmitters and apparatus for line telephony and line telegraph</td>
<td>1.6%</td>
</tr>
<tr>
<td>3150</td>
<td>Manufacture of electric lamps and lighting equipment</td>
<td>1.5%</td>
</tr>
<tr>
<td>3430</td>
<td>Manufacture of parts and accessories for motor vehicles and their engines</td>
<td>1.5%</td>
</tr>
</tbody>
</table>

*ISIC3 industries aggregated to ensure the industry concordances (ISIC3 x CNAE) are consistent.

Notes: UN Comtrade Data, 2013.
### Table 2.11: Industry Shares of Total Exports to China (Largest 20), 2013

<table>
<thead>
<tr>
<th>ISIC3 Code</th>
<th>ISIC3 Description</th>
<th>Share of Exports</th>
</tr>
</thead>
<tbody>
<tr>
<td>1310</td>
<td>Mining of iron ores</td>
<td>39.8%</td>
</tr>
<tr>
<td>0110*</td>
<td>Growing of crops, market gardening, horticulture</td>
<td>36.6%</td>
</tr>
<tr>
<td>1110</td>
<td>Extraction of crude petroleum and natural gas</td>
<td>7.0%</td>
</tr>
<tr>
<td>2101</td>
<td>Manufacture of pulp, paper and paperboard</td>
<td>3.4%</td>
</tr>
<tr>
<td>1542</td>
<td>Manufacture of sugar</td>
<td>2.6%</td>
</tr>
<tr>
<td>1911</td>
<td>Tanning and dressing of leather</td>
<td>1.3%</td>
</tr>
<tr>
<td>2710</td>
<td>Manufacture of basic iron and steel</td>
<td>1.1%</td>
</tr>
<tr>
<td>1300*</td>
<td>Mining of uranium and thorium ores; mining of non-ferrous metal ores</td>
<td>1.1%</td>
</tr>
<tr>
<td>1514</td>
<td>Manufacture of vegetable and animal oils and fats</td>
<td>1.0%</td>
</tr>
<tr>
<td>1511</td>
<td>Production, processing, and preserving of meat and meat products</td>
<td>0.9%</td>
</tr>
<tr>
<td>2720</td>
<td>Manufacture of basic precious and non-ferrous metals</td>
<td>0.8%</td>
</tr>
<tr>
<td>3691</td>
<td>Manufacture of jewellery and related articles</td>
<td>0.7%</td>
</tr>
<tr>
<td>1410</td>
<td>Quarrying of stone, sand and clay</td>
<td>0.5%</td>
</tr>
<tr>
<td>2413</td>
<td>Manufacture of plastics in primary forms and of synthetic rubber</td>
<td>0.4%</td>
</tr>
<tr>
<td>3530</td>
<td>Manufacture of aircraft and spacecraft</td>
<td>0.4%</td>
</tr>
<tr>
<td>2423</td>
<td>Manufacture of pharmaceuticals, medicinal chemicals and botanical products</td>
<td>0.3%</td>
</tr>
<tr>
<td>2411</td>
<td>Manufacture of basic chemicals, except fertilizers and nitrogen compounds</td>
<td>0.3%</td>
</tr>
<tr>
<td>1513</td>
<td>Processing and preserving of fruit and vegetables</td>
<td>0.2%</td>
</tr>
<tr>
<td>9999</td>
<td>Goods not elsewhere classified</td>
<td>0.2%</td>
</tr>
<tr>
<td>2912</td>
<td>Manufacture of pumps, compressors, taps and valves</td>
<td>0.2%</td>
</tr>
</tbody>
</table>

*ISIC3 industries aggregated to ensure the industry concordances (ISIC3 x CNAE) are consistent.

Notes: UN Comtrade Data, 2013.
Table 2.12: Microregion Summary Statistics for Control Variables, 2013

<table>
<thead>
<tr>
<th></th>
<th>(1)</th>
<th>(2)</th>
<th>(3)</th>
<th>(4)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Percent Employment Traded Sectors_1</td>
<td>47.34</td>
<td>16.84</td>
<td>3.13</td>
<td>90.93</td>
</tr>
<tr>
<td>Percent Employment Female_1</td>
<td>29.60</td>
<td>7.64</td>
<td>5.06</td>
<td>47.28</td>
</tr>
<tr>
<td>Percent Employment High School Educated_1</td>
<td>44.11</td>
<td>11.80</td>
<td>8.56</td>
<td>80.28</td>
</tr>
<tr>
<td>Percent Employment Routine Jobs_1</td>
<td>28.42</td>
<td>7.26</td>
<td>5.96</td>
<td>49.80</td>
</tr>
<tr>
<td>Percent Employment Foreign Born_1</td>
<td>0.04</td>
<td>0.08</td>
<td>0.00</td>
<td>1.23</td>
</tr>
<tr>
<td>Average Offshore Index_1</td>
<td>0.36</td>
<td>0.23</td>
<td>-0.32</td>
<td>1.73</td>
</tr>
</tbody>
</table>

*Notes: Summary statistics for microregion start of period control variables. RAIS Data, 2008.*
Figure 2.3: Brazil’s Trade Patterns with the World and with China, 1992-2013

(a) Brazil’s Trade with the World

(b) Brazil’s Trade with China

Notes: UN Comtrade Data, 1992-2013. Value of total trade presented in billions of USD. The vertical line at the year 2001 indicates the year China officially joined the WTO.
Figure 2.4: Brazil’s Trade with the World and with China as Share of GDP, 1992-2013

(a) Brazil’s Trade with the World as Share of GDP

(b) Brazil’s Trade with China as Share of GDP

Notes: UN Comtrade Data, 1992-2013. Value of total trade presented in billions of USD. The vertical line at the year 2001 indicates the year China officially joined the WTO.
CHAPTER 3

LABOR MARKET REALLOCATION AND TRADE WITH CHINA: THE CASE OF BRAZIL (WITH PETER BRUMMUND)

3.1 Introduction

Countries around the world have increasingly opened their borders to international trade. Developing countries in particular have integrated into the world economy in hopes of creating more sustainable economic growth. For example, Brazil liberalized their trade policies in the early 1990’s as a means for consistent economic growth. However, countries have recently experienced some push back on trade openness policies due to the belief that trade harms domestic production and domestic workers. Former President of Brazil Dilma Rousseff, in response to trade openness concerns, introduced a series of defensive trade policies during her first year in office in 2011. Rousseff intended for the restrictive trade policies to boost domestic production and innovation as well as curb fears of deindustrialization in Brazil. While trade critics typically blame increased imports for declining domestic production, they often ignore the potential benefits from increased exports.

In this paper, we explore both aspects of Brazil’s trade relationship with China and their effects on migration and labor reallocation in Brazil. More specifically, we analyze the impact of increased imports from China and increased exports to China on labor reallocation across industries and geographic regions in Brazil. We link administrative panel data for the formal labor market in Brazil for the years 2004 to 2013 with UN Comtrade data for Brazil, China, and other countries. Following the instrumental variable approach of Autor, Dorn, and Hanson (2013), we instrument for Brazil’s trade with China.
using other countries’ trade with China to eliminate endogeneity concerns common in the trade and labor literature. We focus on the impact of the China trade shock on: (1) migration across microregions in Brazil, (2) labor reallocation from the formal sector to nonemployment within microregions, and (3) labor reallocation from nonemployment to the formal sector within microregions.

For developing countries like Brazil, the informal sector is also a large part of the economy. While the proportion of workers in the informal sector in Brazil has consistently declined since 1999, 37% of Brazilian workers were still employed in the informal sector in 2013 (Cardoso, 2016). However, employment in the formal sector provides workers with benefits mandated by the government, such as minimum wages, maximum work hours, and annual bonuses pending eligibility. Additionally, informal workers in Latin American countries on average work more hours, earn lower wages, work in less safe conditions, and are in more vulnerable positions in the labor market (Cardoso, 2016). Therefore, we consider worker flows from nonemployment to employment in the formal sector to be a positive reallocation for workers and flows from employment in the formal sector to nonemployment to be a negative reallocation for workers. In this paper, we investigate the relationship between globalization, focusing on Brazil’s trade with China, and labor market reallocation into (or out of) the formal sector in Brazil. We anticipate that exports to China will be associated with labor reallocation that is beneficial to workers while imports from China will be associated with labor flows that are harmful to workers.

This paper contributes to two distinct areas of the trade and labor literature. First, we contribute to the emerging literature on the economic effects of China’s rise on labor market outcomes in other countries. Several papers document the effect of China’s unprecedented economic growth and dominance in certain world trade markets, particularly for manufacturing products, on labor market outcomes in various countries. While these papers dominantly analyze local labor market outcomes such as employment or wages, we analyze labor market reallocation and migration. The administrative panel
data we use, a matched employer-employee data set, allows us to accurately calculate labor market reallocation and migration by following individual workers over time.\footnote{Most studies do not have data that is suitable for studying labor market reallocation and migration.} Additionally, most papers in the literature focus on the impact of increased imports from China. However, Brazil simultaneously experienced a rapid increase in imports from China and exports to China.\footnote{From 1992 to 2013, Brazil simultaneously increased their share of total imports from China by 14 percentage points and increased their share of total exports to China by 21 percentage points.} This trade pattern was not exclusive to Brazil and China; several other developing countries also experienced similar trade patterns with China. Therefore, it is important to analyze both imports and exports to fully capture the effect of China’s rise on labor markets in other developing countries.

We also contribute to the area of literature that focuses on the effects of globalization in developing countries, specifically Brazil. As Brazil continues to economically progress, it is important to analyze the role of trade in labor market dynamics, particularly since Brazil is one of the top 10 largest economies in the world. As part of its attempt to economically advance, Brazil has emphasized the need to shrink the informal sector and to grow the formal sector. Employment in traded sectors is more likely to be in the formal sector, particularly for the manufacturing and mining sectors. Therefore, we explore the relationship between Brazil’s trade with China and employment flows into and out of formal sector employment. Further, it is often debated whether Brazil and China are partners in their attempts to become world powers or competitors trying to beat each other to power (Pereira & de Castro Neves, 2011). Therefore, it is worthwhile to examine a potential channel through which Brazil’s trade with China is affecting workers in Brazil.

Overall, we find that the results for migration generally match our predictions. Microregions more exposed to increased exports to China have higher migration rates. We find the opposite result for imports; microregions more exposed to imports from China have lower migration rates. Together, these results suggest that areas exposed to exports
attract more new workers, likely because exports are creating more labor market opportunities. For our sample of analysis, 2008 to 2013, migration rates are relatively low at 4%. With only 4% of workers migrating to a different microregion for employment, trade with China has a relatively large effect in terms of magnitude. A microregion at the 75th percentile of Chinese export exposure experienced migration rates 1.25 percentage points higher in comparison to a microregion at the 25th percentile. A similar comparison for imports shows that a microregion at the 75th percentile for imports had migration rates 0.5 percentage points lower than a microregion at the 25th percentile. The migration results largely support our hypothesis that exports will reallocate workers in a positive manner while imports will reallocate workers in a negative manner.

The results for industry reallocation are much less consistent than the migration results. We find that export exposure typically does not have a significant effect on reallocation into or out of nonemployment. We also find that import exposure has a negative and significant relationship with reallocation from the traded sector to nonemployment, which is a beneficial transition for workers. In contrast, imports also have a negative and significant relationship with reallocation from nonemployment to employment in the nontraded sector. We only find one instance where export exposure significant affects labor reallocation in a positive manner. Microregions more exposed to exports to China have higher labor flows from nonemployment to employment in the mining sector. However, we also find that exports increase labor flows from employment in the mining sector to nonemployment. These results indicate that employment in the mining sector is relatively volatile. Overall, the results do not clearly indicate that imports are associated with labor flows that are harmful to workers while exports are associated with labor flows that are beneficial to workers. In fact, imports are more associated with labor flows that are beneficial to workers in Brazil.

This paper will proceed as follows. Section 3.2 gives a brief overview of the literature and Section 3.3 details the methodology used for the analysis. Section 3.4
describes the data and presents summary statistics. Section 3.5 discusses the main results. Last, Section 3.6 offers concluding remarks.

3.2 Literature Review

3.2.1 Labor Reallocation in Brazil

Dix-Carneiro and Kovak (2017b) analyze labor market reallocation in Brazil in the aftermath of Brazil’s trade liberalization in the early 1990’s. The authors use both administrative panel data for the formal labor market and Demographic Census data to study worker reallocation from 1991 to 2010 between the formal sector, the informal sector, and nonemployment. Dix-Carneiro and Kovak’s (2017b) findings indicate that workers employed in regions more exposed to reduced tariffs are more likely to transition to employment in the nontraded sector, nonemployment in the medium run, or the informal sector in the long run. However, there are no significant effects of trade liberalization on regional migration in Brazil.

Menezes-Filho and Muendler (2011) also study labor reallocation in Brazil in response to Brazil’s trade liberalization. The authors find that large tariff declines associated with Brazil’s trade liberalization triggered worker displacements. Similar to Dix-Carneiro and Kovak (2017b), Menezes-Filho and Muendler (2011) find that trade liberalization causes workers to reallocate to unemployment, service sectors, or out of the labor force entirely. The aim of this paper is to further investigate the role of trade in labor market reallocation in Brazil. However, rather than Brazil’s trade liberalization, we use the China trade shock to account for the effect of both imports and exports. In contrast to Brazil’s trade liberalization shock which was discrete, the China trade shock is continuous. Therefore, by studying a continuous trade shock that captures both trade flows, it is possible that the China trade shock will affect migration rates and employment flows in

\footnote{See Dix-Carneiro and Kovak (2017b) or Dix-Carneiro and Kovak (2017a) for details of Brazil’s trade liberalization.}
Brazil in a different manner than Brazil’s trade liberalization.

3.2.2 Labor Market Responses to Trade with China

The unique supply-driven growth of China has been felt by countries around the world. The country has increased their share of worldwide production, particularly in manufacturing products, leading other countries’ to increasingly rely on Chinese imports. China’s economic rise and subsequent impact on labor market outcomes in other countries has become an increasingly popular branch of the trade and labor literature. This area of research, made popular by Autor et al. (2013), largely focuses on the impact of increased imports from China on manufacturing labor market outcomes in other countries. The literature to date generally agrees that China’s rise and dominance in certain trade markets, deemed the “China trade shock,” harms workers employed in import competing industries in other countries (see Autor et al. (2013) for the US, Costa, Garred, and Pessoa (2016) for Brazil, Mion and Zhu (2013) for Belgium, and Iacovone, Rauch, and Winters (2013) for Mexico).

The negative impacts of increased imports from China have further fueled trade critics’ claims against trade openness policies and trade with China specifically. Brazilian manufacturers pointed to China’s extremely cheap labor costs, low labor standards, and high presence of state-owned enterprises (SOEs) in their argument against Brazil’s reliance on imports from China (Menendez, 2014). As previously mentioned, former President of Brazil Dilma Rousseff implemented several defensive trade policies in 2011 in response to criticism against free trade policies. Rousseff intended for the restrictive trade policies to boost domestic production and innovation as well as curb fears of deindustrialization in Brazil. Businesses and some policymakers supported the defensive trade policies. They believed Brazil should focus on increasing its competitiveness by focusing on

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4China’s growth has been fueled by internal economic changes due to their transition from a central-planning to a market-based economy. China’s accession to the World Trade Organization (WTO) in 2001 also triggered a massive increase in the country’s presence in international markets.

5Erten and Leight (2017) calculate that China’s share of worldwide manufacturing exports increased from 3% to 17% from 1996 to 2013.
“...value-added and the technology component of export[s]” (Doctor, 2012, p. 806), rather than commodity exports. The fear of deindustrialization in Brazil is merely one example of the increasing sentiment among developing countries that are reliant on commodity exports. Further, China has increased its dependence on commodity exports from other countries in response to continued economic growth.  

A smaller branch of the literature analyzes the effect of both increased imports from China and increased exports to China. In response to China’s economic growth, countries not only rapidly increased their imports from China, but, developing countries in particular, also took advantage of the expanding export market in China. For example, Brazil increased both the value of their imports from China and their exports to China during the 2000’s. Costa et al. (2016) analyze the effect of both the supply side of increased imports from China and the demand side of increased exports to China on local labor market outcomes in Brazil from 2000 to 2010. The authors find that microregions more exposed to increased exports to China experienced higher wage growth, but microregions more exposed to increased imports from China experienced lower wage growth. In this paper, we build upon Costa et al.’s (2013) work by studying the impact of trade with China on labor market reallocation and migration in Brazil rather than labor market outcomes such as employment and wages. We also use administrative panel data, rather than demographic census data, that allows us to follow individual workers over time, which is key for accurately capturing labor market dynamics.

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6Commodity exports often inflate a country’s currency, decreasing the competitiveness of manufacturing and agriculture products. This eventually leads to increasing imports, decreasing exports, and balance-of-payment problems, all of which are associated with poor economic performance (Gallagher, 2010).

7A microregion is commonly used to define a local labor market in Brazil and is similar to a commuting zone in the United States. Other papers in the literature that define a local labor market in Brazil using a microregion include: Dix-Carneiro and Kovak (2017a, 2017b), Kovak (2013), and Gaddis and Pieters (2017).
3.3 Methodology

The method we use in this paper is closely related to Autor et al.’s (2013) instrumental variable approach. Autor et al. (2013) analyze the effect of increased imports from China on US local labor market outcomes and instrument for US imports from China using other countries’ imports from China. Therefore, the basic idea is to instrument for Brazil’s trade with China (imports and exports) using other countries trade with China.

The underlying assumption behind the instrumental variable approach is that China’s unprecedented economic growth is due to changing internal conditions in China. Therefore, China’s dominance in certain trade markets and rising trade values should be common across countries. There are two key trade variables of interest for the analysis. The first, the change in Chinese import exposure per worker in Brazil $b$ for microregion $i$ in year $t$ is defined as follows:

$$
\Delta IPW_{bit} = \sum_j \frac{L_{ijt}}{L_{bit}} \frac{\Delta M_{bcjt}}{L_{bit}},
$$

where $L_{ijt}$ is employment in microregion $i$ in industry $j$ in year $t$, $L_{bit}$ is national employment in industry $j$ in year $t$ in Brazil $(b)$, and $L_{bit}$ is total employment in microregion $i$ in year $t$. $\Delta M_{bcjt}$ is the change in imports from China $(c)$ to Brazil $(b)$ in industry $j$ from year $t$ to $t+1$.\(^8\) The change in Chinese import exposure per worker measure is the sum of Brazil’s imports from China across all industries, weighted by the initial industry and microregion employment shares. Therefore, the variation in the change in Chinese import exposure variable comes directly from different employment levels across microregions, $i$, and industries, $j$, in Brazil.

However, the change in import exposure per worker in Brazil measure is likely endogenous to labor market outcomes in Brazil. For example, labor in Brazil could have reallocated due to supply or demand shocks that we cannot observe in the data. For

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\(^8\)Equation (3.1) is analogous to Equation (3) in Autor et al. (2013).
example, if increased imports of consumer electronics stem from changing consumer demand in Brazil, rather than decreased trade costs and increased comparative advantage in China, then the estimates will likely underestimate the true effect of increased imports from China (Autor et al., 2013). Therefore, it is necessary to use an instrumental variable, following Autor et al. (2013), as previously described. The instrumental variable, the change in Chinese import exposure in other countries per worker, is calculated as follows:

$$\Delta IPW_{oit} = \sum_j \frac{L_{ijt-1}}{L_{bjt-1}} \frac{\Delta M_{ocjt}}{L_{it-1}}$$

(3.2)

where $L_{ijt-1}$ measures the employment in microregion $i$ in industry $j$ from the start of the previous period $t-1$, $L_{bjt-1}$ is national employment in industry $j$ in Brazil ($b$) from the start of the previous period $t-1$, and $L_{it-1}$ is total employment in microregion $i$ from the start of the previous period $t-1$. $\Delta M_{ocjt}$ measures the change in imports from China ($c$) to other countries ($o$) in industry $j$ from year $t$ to year $t+1$. The instrumental variable uses lagged employment levels to account for the possibility that employment changes in Brazil occurred in response to anticipated increased imports from China.

So far, the key trade variable of interest and the instrumental variable are directly from Autor et al. (2013). We now extend the methodology to account for Brazil’s exports to China. The second trade variable of interest for Brazil, the change in exports to China from Brazil per worker in microregion $i$ in year $t$ is calculated as follows:

$$\Delta EPW_{bit} = \sum_j \frac{L_{ijt}}{L_{bjt}} \frac{\Delta E_{bcjt}}{L_{it}}$$

(3.3)

where $L_{ijt}$, $L_{bjt}$, and $L_{it}$ are previously defined in equation (3.1) and $\Delta E_{bcjt}$ is the change in exports to China ($c$) from Brazil ($b$) in industry $j$ from year $t$ to year $t+1$. Again, the variation in the export exposure measure stems directly from different industry and
microregion employment structures in Brazil.

However, endogeneity issues are also likely to affect the export exposure variable. Given the commodity boom that occurred during the early 2000’s, it is likely that Brazil’s increased exports to China are partially in response to supply shocks in Brazil. Therefore, we extend the instrumental variable in equation (3.2) to also account for exports to China. The second instrumental variable, the change in Chinese export exposure per worker in other countries, is calculated as follows:

$$\Delta EPW_{oit} = \sum_j \frac{L_{ijt-1} \Delta E_{ocjt}}{L_{bijt-1} L_{it-1}},$$

(3.4)

where $L_{ijt-1}$, $L_{bijt-1}$, and $L_{it-1}$ are previously defined in equation (3.2). $\Delta E_{ocjt}$ measures the change in exports to China $c$ from other countries $o$ in industry $j$ from year $t$ to year $t+1$. The instrumental variable again uses lagged employment levels to account for possible simultaneity bias. We use a mix of Latin American and other developing countries in the instrumental variable to account for the fact that several Latin American countries also experienced a commodity boom during the 2000’s.

For all analysis, we use a two-stage least squares model to determine the impact of Brazil’s trade with China on migration and labor reallocation in Brazil, instrumenting for both of Brazil’s trade with China exposure variables using other countries’ trade with China. The general 2SLS method is outlined below.

$$\log(Y_{it}) = \alpha_0 + \beta_0 \Delta IPW_{bit} + \gamma_0 \Delta EPW_{bit} + \lambda_0 X_t + \epsilon_t,$$

(3.5)

where the first stage models are estimated as follows:

$$\Delta IPW_{bit} = \alpha_1 + \beta_1 \Delta IPW_{oit} + \gamma_1 \Delta EPW_{oit} + \lambda_1 X_{it} + \epsilon_{it},$$

(3.6)

$$\Delta EPW_{bit} = \alpha_2 + \beta_2 \Delta IPW_{oit} + \gamma_2 \Delta EPW_{oit} + \lambda_2 X_{it} + \epsilon_{it}.$$

(3.7)

\[11\] Export IV countries include: Chile, Colombia, Mexico, Peru, South Africa, Thailand, Uruguay, and Venezuela.
\( Y_{it} \) represents various reallocation variables that measure micoregion \( i \) labor reallocation rates or flows from year \( t \) to year \( t+1 \), \( X_{it} \) is a vector of micoregion-specific start of period controls. \( \Delta IPW_{bit}, \Delta EPW_{bit}, \Delta IPW_{oit}, \) and \( \Delta EPW_{oit} \) are previously defined in equations (3.1), (3.2), (3.3), and (3.4), respectively. All regressions are weighted by the micoregion share of national employment at the start of the period, \( t \), and standard errors are clustered at the state level. First stage regressions also include all micoregion-specific start of period controls included in the second stage.

The main variables of interest in the analysis are migration and various forms of industry reallocation within Brazilian microregions from year \( t \) to year \( t+1 \). The labor market reallocation variables are calculated as the number (or percentage) of workers in a micoregion who changed their industry (or microregion) of employment from year \( t \) to \( t+1 \). Therefore, we initially calculate labor market reallocation at the worker level from year \( t \) to \( t+1 \) and then aggregate this measure up to the micoregion level. For example, one variable of interest in the analysis is the number of workers within a micoregion that transitioned from nonemployment in 2008, year \( t \), to employment in the traded sector in 2013, year \( t+1 \). For this specific worker-level transition, we define \( nonemp_{to\_trade}_{wit} \) for each worker \( w \) in micoregion \( i \) form year \( t \) to year \( t+1 \) as follows:

\[
nonemp_{to\_trade}_{wit} = \begin{cases} 
1 & \text{if nonemployed in } t-1 & \text{& employed in traded sector in } t \\
0, & \text{otherwise}
\end{cases}
\]

We then calculate the number of workers within a micoregion that reallocated from nonemployment in 2008, year \( t \), to employment in the traded sector in 2013, year \( t+1 \). We define \( micro_{nonemp\_to\_trade}_{it} \) for each micoregion \( i \) in year \( t \) as follows:

\[
micro_{nonemp\_to\_trade}_{it} = \sum_{w \in i} nonemp_{to\_trade}_{wit},
\]
Table 3.1: List of Labor Reallocation Flows, 2008-2013

<table>
<thead>
<tr>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>Migration</td>
<td>Microregion_A</td>
<td>Microregion_B</td>
</tr>
<tr>
<td>Traded to Nontraded Sector</td>
<td>Traded</td>
<td>Nontraded</td>
</tr>
<tr>
<td>Traded Sector to Nonemployment</td>
<td>Traded</td>
<td>Nonemp</td>
</tr>
<tr>
<td>Nonemployment to Traded Sector</td>
<td>Nonemp</td>
<td>Traded</td>
</tr>
<tr>
<td>Nonemployment to Nontraded Sector</td>
<td>Nonemp</td>
<td>Nontraded</td>
</tr>
<tr>
<td>Nonemployment to Manufacturing</td>
<td>Nonemp</td>
<td>Manf</td>
</tr>
<tr>
<td>Nonemployment to Agriculture</td>
<td>Nonemp</td>
<td>Agric</td>
</tr>
<tr>
<td>Manufacturing to Nonemployment</td>
<td>Manf</td>
<td>Nonemp</td>
</tr>
<tr>
<td>Agriculture to Nonemployment</td>
<td>Agric</td>
<td>Nonemp</td>
</tr>
<tr>
<td>Mining to Nonemployment</td>
<td>Mining</td>
<td>Nonemp</td>
</tr>
</tbody>
</table>

In the analysis, we focus on labor market reallocation measures from the formal sector to nonemployment or from nonemployment to the formal sector. Due to the nature of our data, nonemployment includes unemployment, employment in the informal sector, and those no longer in the labor market. However, we can only observe nonemployment for workers who are in the data at some point during our sample. For each transition, we follow the methodology outlined above. First, we calculate the transition at the worker-level using a dummy variable equal to one if the worker $w$ transitioned from A to B from year $t$ to $t+1$ and equal to zero otherwise. Then, we calculate the number of workers within a microregion $i$ that reallocated from option A in year $t$ to option B in year $t+1$. A list of all labor reallocation flows included as dependent variables is presented in Table 3.1.

### 3.4 Data

The data for this project comes from two sources: (1) labor market data for Brazil, and (2) trade data for Brazil, China, and other countries. We use an administrative panel data...
data set for the formal labor market in Brazil, the *Relação Anual de Informações Sociais* (RAIS), for the years 2004 through 2013. The RAIS data set is a matched employer-employee data set collected annually by the Brazilian Ministry of Labor (MTE). An observation in the RAIS data set is defined at the worker level using a worker identification number, which is linked to an establishment identification number and detailed worker and establishment information. The RAIS data has several advantages for this project. First, the linked nature of the data allows us to accurately track individual workers across time. Second, the RAIS also contains detailed worker characteristics and some establishment characteristics, such as industry, geographic region, occupation, age, hire date, and education, among others. Last, RAIS is considered a high quality data set and theoretically covers the entire formal labor market in Brazil (Dix-Carneiro & Kovak, 2017a).

The unit of analysis is a microregion, our definition of a local labor market in Brazil. We first use the detailed worker-level data to track workers across time, creating a series of dummy variables to track various labor reallocation flows. Then, we aggregate the worker-level data to calculate the number (percentage) of workers within a microregion who switched their industry of employment (migrated). This provides us with microregion-level migration and labor reallocation variables that accurately capture worker movements within and across Brazil over time. Data analysis tracks movement from 2008 to 2013 and the instrumental variables use lagged employment levels from 2004.

The trade data comes from the UN Comtrade database which keeps trade data for over 150 countries. Since countries often care more about what comes into a country rather than what leaves a country, import data is considered more accurate than export data. Therefore, we use only import data to ensure consistency of the trade data. For example, for Brazil’s exports to China, we use data on China’s imports from Brazil. For Brazil’s imports from China, we use data on Brazil’s imports from China. We use UN Comtrade data for the years 2008 to 2013, all of which is reported at the 6-digit product level using
the Harmonized Tariff System (HS).

However, in order to link the UN Comtrade data to the RAIS data, it is necessary to aggregate the product-level trade data up to industry-level trade data. We follow the standard approach in the literature and map each 6-digit product code to a 4-digit industry code (ISIC; International Standard Industrial Classification System).\(^{13}\) The RAIS data follows Brazil’s National Classification of Economic Activities (CNAE) to classify each workers industry of employment. Therefore, it is also necessary to map each ISIC industry to one CNAE industry to link the two data sets. The Brazilian Institute of Geography and Statistics (IBGE) provides concordances for these two industry classification systems. However, when necessary, we aggregate industries to ensure a one to one match.\(^{14}\)

The summary statistics for worker-level migration and industry reallocation from 2008 to 2013 are presented in Table 3.2. The table shows that approximately 4% of all workers employed in the formal sector in 2008 migrated to a different microregion for employment in 2013. In the same five year span, 2008-2013, approximately 16% of all workers employed in the formal sector changed their industry of employment. The remaining summary statistics for different types of worker reallocation from 2008 to 2013 are interpreted as the percentage of all workers in the base category in 2008 that switched to the second category in 2013. For example, “Employed (2008) to Nonemployed (2013)” indicates that 44.7% of all workers employed in the formal sector in 2008 transitioned to nonemployment in 2013; “Manufacturing (2008) to Nonemployed (2013)” indicates that 43.2% of all manufacturing workers in 2008 transitioned to nonemployment in 2013. Due to the structure of the RAIS data, we can observe when a worker leaves the formal sector and enters nonemployment. However, we cannot distinguish between different options of nonemployment: unemployed, out of the labor force, or informal employment.

When we focus on the subpopulation of workers who were nonemployed in 2008 and

\(^{13}\)We use concordances from the World Bank’s Integrated Trade Solutions to map 6-digit HS product codes to 4-digit ISIC industry codes. Concordances are available at http://wits.worldbank.org/product_concordance.html.

\(^{14}\)The final industry concordances for CNAE to ISIC are available upon request.
transitioned to employment in the formal sector in 2013, nearly 41% transitioned to employment in the traded sector while 59% transitioned to employment in the nontraded sector. Due to the employee benefits guaranteed to workers in the formal sector, we consider worker transitions out of nonemployment into formal employment to be positive. For the same reason, we consider worker transitions out of the formal sector into nonemployment to be negative. Table 3.2 also reveals that labor market reallocation at the worker-level is relatively high in Brazil.

Table 3.3 shows the summary statistics for the two trade exposure variables and the two instrumental variables, the change in Chinese import (export) exposure per worker in Brazil and the change in Chinese import (export) exposure per worker in other countries.
Table 3.3: Summary Statistics: Trade Exposure Measures, 2008-2013

<table>
<thead>
<tr>
<th></th>
<th>(1)</th>
<th>(2)</th>
<th>(3)</th>
<th>(4)</th>
<th>(5)</th>
<th>(6)</th>
<th>(7)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>p25</td>
<td>p50</td>
<td>p75</td>
<td>mean</td>
<td>sd</td>
<td>min</td>
<td>max</td>
</tr>
<tr>
<td>Δ Imports from China to Brazil per worker ($IPW_{bit}$)</td>
<td>85</td>
<td>183</td>
<td>357</td>
<td>269</td>
<td>424</td>
<td>-3,740</td>
<td>3,335</td>
</tr>
<tr>
<td>Δ Imports from China to other countries per worker ($IPW_{oit}$)</td>
<td>435</td>
<td>913</td>
<td>1,711</td>
<td>1567</td>
<td>3,022</td>
<td>-1,185</td>
<td>21,987</td>
</tr>
<tr>
<td>Δ Exports to China from Brazil per worker ($EPW_{bit}$)</td>
<td>110</td>
<td>381</td>
<td>1,362</td>
<td>1349</td>
<td>3,464</td>
<td>-2,774</td>
<td>53,481</td>
</tr>
<tr>
<td>Δ Exports to China from other countries per worker ($EPW_{oit}$)</td>
<td>333</td>
<td>946</td>
<td>2,401</td>
<td>4071</td>
<td>16,325</td>
<td>-345</td>
<td>78,072</td>
</tr>
</tbody>
</table>

Notes: Calculated using UN Comtrade data for the years 2008 and 2013 and RAIS data for the years 2004-2013. p# indicates the #th percentile. Import IV countries include: Argentina, Chile, Colombia, Indonesia, Peru, South Africa, Thailand, and Uruguay. Export IV countries include: Chile, Colombia, Mexico, Peru, South Africa, Thailand, Uruguay, and Venezuela.

Table 3.3 indicates that the average change in imports from China to Brazil per worker from 2008 to 2013 was approximately $270. The average change in exports to China from Brazil per worker for the same time period was approximately $1,350. Further, the table also highlights the variation in exposure to trade with China based on a worker’s microregion of employment. For example, a microregion at the 75th percentile of import exposure experienced nearly a $360 increase in imports from China while a microregion at the 25th percentile only experienced an $85 increase. The pattern is similar, but even larger in magnitude for exports. A microregion at the 75th percentile of export exposure experienced a $1,350 increase in exports while a microregion at the 25th percentile only experienced a $110 increase in exports.

The two instrumental variables, the trade exposure variables using trade data from other countries, also have similar variation. While the instrumental variables are larger in magnitude, this is due to the fact that the instrumental variables include trade values aggregated across eight countries while the trade variables for Brazil only include trade values for Brazil. The variation in trade exposure for imports from China and exports to...
Table 3.4: First Stage Results, 2008-2013

<table>
<thead>
<tr>
<th></th>
<th>ΔIPW&lt;sub&gt;bit&lt;/sub&gt;</th>
<th>ΔEPW&lt;sub&gt;bit&lt;/sub&gt;</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>(1)</td>
<td>(2)</td>
</tr>
<tr>
<td>Δ Imports from China to</td>
<td>0.180***</td>
<td>-0.012</td>
</tr>
<tr>
<td>other countries per worker</td>
<td>(0.020)</td>
<td>(0.045)</td>
</tr>
<tr>
<td>Δ Exports to China from</td>
<td>0.000</td>
<td>0.185**</td>
</tr>
<tr>
<td>other countries per worker</td>
<td>(0.003)</td>
<td>(0.089)</td>
</tr>
<tr>
<td>N</td>
<td>557</td>
<td>557</td>
</tr>
<tr>
<td>R&lt;sup&gt;2&lt;/sup&gt;</td>
<td>0.697</td>
<td>0.412</td>
</tr>
</tbody>
</table>

Notes: Change in import and export exposure variables are calculated as the change from 2008 to 2013. All models include a constant, region controls, controls for the initial microregion percent employment high school educated, foreign born, in routine jobs, in traded sectors, and initial average offshorability index. Standard errors in parentheses are clustered at the state level and models are weighted by 2008 microregion employment shares. * p<0.10, ** p<0.05, *** p<0.01

China across Brazilian microregions further highlights the identification strategy. The analysis will compare microregions more exposed to trade with China to those less exposed to trade with China. Therefore, the results can be interpreted as a local treatment effect.

### 3.5 Results

Before presenting the results for the main analysis, it is worthwhile to first confirm the validity of the instrumental variables. The results for the first stage regressions are presented in Table 3.4. The coefficient of 0.18 in column (1) is positive and significant at the one percent level. This indicates that the change in Chinese imports per worker in other countries predicts the change in Chinese imports per worker in Brazil. Similarly, the coefficient of 0.185 in column (2) is also positive and significant, which shows that the change in Chinese exports per worker in other countries predicts the change in Chinese exports in Brazil. The first stage regressions also include control variables for microregion characteristics from the start of the period that are included in the second stage regressions. Control variables are listed in the note in Table 3.4.

Table 3.5 presents the results for migration across microregions in Brazil and trade
with China. In addition to the control variables presented in Table 3.5, the analysis also includes region controls and a constant. The two key variables of interest are the change in Chinese import exposure per worker in Brazil and the change in Chinese export exposure per worker in Brazil (both of which have been instrumented for using the two IVs previously defined). The coefficient of -0.002 associated with imports indicates that an increase in Chinese import exposure decreases the percentage of workers who migrate into a region. This negative relationship is also statistically significant at the ten percent level. For a microregion with average exposure to the change in Chinese imports, this corresponds to a decline in migration of approximately 0.5 percentage points. An alternative way to interpret this result is to compare a microregion at the 75th percentile of import exposure to a microregion at the 25th percentile. A microregion at the 75th percentile experienced a migration rate 0.5 percentage points lower than a microregion at the 25th percentile. This translates to a difference of approximately 350 workers.

The coefficient of 0.001 in the second row indicates that the change in Chinese export exposure per worker in Brazil is positively related to migration. The effect is also highly significant at the one percent level. For the average microregion, this translates to an increase in the migration rate of 1.35 percentage points in response to increased exports to China. When we compare a microregion at the 75th percentile of Chinese export exposure to one at the 25th percentile, this translates to a higher migration rate of 1.25 percentage points. Given that only 4 percent of workers migrated to a different microregion for employment from 2008 to 2013, these increases are relatively large and economically significant. Table 3.5 also shows that only the initial microregion percent of employment in traded sectors and the initial microregion percent of female employment significantly affect migration rates. Microregions with a higher percentage of workers in the traded sector have higher migration rates while microregions with a higher percentage of female workers have lower migration rates. Overall, Table 3.5 indicates that microregions more exposed to imports from China attract fewer new employees while microregions more exposed to
Table 3.5: Migration Across Microregions and Trade with China, 2008-2013

<table>
<thead>
<tr>
<th>Migration</th>
<th>(1)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Δ Imports from China to Brazil per worker</td>
<td>-0.002*</td>
</tr>
<tr>
<td></td>
<td>(0.001)</td>
</tr>
<tr>
<td>Δ Exports to China from Brazil per worker</td>
<td>0.001***</td>
</tr>
<tr>
<td></td>
<td>(0.000)</td>
</tr>
<tr>
<td>Percent Employment Traded Sectors</td>
<td>0.099*</td>
</tr>
<tr>
<td></td>
<td>(0.060)</td>
</tr>
<tr>
<td>Percent Employment Female</td>
<td>-0.332***</td>
</tr>
<tr>
<td></td>
<td>(0.067)</td>
</tr>
<tr>
<td>Percent Employment High School Educated</td>
<td>-0.034</td>
</tr>
<tr>
<td></td>
<td>(0.031)</td>
</tr>
<tr>
<td>Percent Employment Foreign Born</td>
<td>4.272</td>
</tr>
<tr>
<td></td>
<td>(3.395)</td>
</tr>
<tr>
<td>Percent Employment Routine Jobs</td>
<td>-0.005</td>
</tr>
<tr>
<td></td>
<td>(0.100)</td>
</tr>
<tr>
<td>Average Offshore Index</td>
<td>-1.178</td>
</tr>
<tr>
<td></td>
<td>(2.023)</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Region</th>
<th>Yes</th>
</tr>
</thead>
<tbody>
<tr>
<td>N</td>
<td>558</td>
</tr>
<tr>
<td>$R^2$</td>
<td>0.3335</td>
</tr>
</tbody>
</table>

Notes: Microregion migration is calculated using the RAIS data for 2008 and 2013. An indicator variable is used to determine whether a worker migrated to a different microregion from 2008 to 2013. Then, Microregion migration is calculated as the percent of all workers who migrated to that microregion. All models also include a constant. Standard errors in parentheses are clustered at the state level. First stage estimates are similar to those in Table 1 and therefore are not included. * p<0.10, ** p<0.05, *** p<0.01

exports to China attract more new employees. These migration results sharply contrast with those of Dix-Carneiro and Kovak (2017b), who found that Brazil’s trade liberalization did not affect migration in Brazil.

Next, we transition from migration to industry reallocation within Brazilian
Table 3.6: Reallocation from the Traded Sector and Trade with China, 2008-2013

<table>
<thead>
<tr>
<th></th>
<th>(1) Traded to Nontraded Sector</th>
<th>(2) Traded Sector to Nonemployment</th>
</tr>
</thead>
<tbody>
<tr>
<td>( \Delta ) Imports from China to Brazil per worker</td>
<td>-0.0004** (0.0002)</td>
<td>-0.0004*** (0.0002)</td>
</tr>
<tr>
<td>( \Delta ) Exports to China from Brazil per worker</td>
<td>-0.0002 (0.0002)</td>
<td>-0.0003 (0.0002)</td>
</tr>
<tr>
<td>Percent Employment Traded Sectors</td>
<td>0.0185 (0.0113)</td>
<td>0.0476*** (0.0077)</td>
</tr>
<tr>
<td>Percent Employment Female</td>
<td>0.0637*** (0.0233)</td>
<td>0.0526*** (0.0187)</td>
</tr>
<tr>
<td>Percent Employment High School Educated</td>
<td>0.0357** (0.0179)</td>
<td>0.0545*** (0.0153)</td>
</tr>
<tr>
<td>Percent Employment Foreign Born</td>
<td>4.6972** (2.3394)</td>
<td>6.0039*** (2.1760)</td>
</tr>
<tr>
<td>Percent Employment Routine Jobs</td>
<td>0.0847*** (0.0242)</td>
<td>0.0589*** (0.0211)</td>
</tr>
<tr>
<td>Average Offshore Index</td>
<td>-2.0858* (1.0656)</td>
<td>-1.7822* (0.9286)</td>
</tr>
</tbody>
</table>

Region: Yes, Yes  
N: 557, 558  
\( R^2 \): 0.6131, 0.7095

Notes: Microregion level industry reallocation is calculated using the RAIS data for 2008 and 2013. An indicator variable is used to determine whether a worker was initially employed in the traded sector (2008) and transitioned to employment in the nontraded sector or nonemployment in 2013. Microregion reallocation is calculated as the number of workers within a microregion who transitioned from the traded sector to the nontraded sector or nonemployment. All models also include a constant. Standard errors in parentheses are clustered at the state level. First stage estimates are similar to those in Table 3.4 and therefore are not included. * \( p < 0.10 \), ** \( p < 0.05 \), *** \( p < 0.01 \)

microregions in response to increased trade with China. Table 3.6 presents the results for the analysis of industry reallocation from the traded sector to the nontraded sector, column (1), or nonemployment, column (2). Both outcome variables are the logarithm of the
number of workers within each microregion who transitioned from the traded sector to either the nontraded sector (1) or nonemployment (2). In addition to the control variables listed in the table, the regressions also include a constant and region controls. The results in column (1) show that microregions more exposed to imports from China have fewer workers reallocate from the traded sector to the nontraded sector. The results in column (2) also show the same pattern for worker reallocation from the traded sector to nonemployment. The coefficient of -0.0004 in both columns indicates that a microregion at the 75th percentile of Chinese import exposure experienced worker reallocation flows from the traded to the nontraded sector or nonemployment approximately 0.12 percentage points lower than a microregion at the 25th percentile.

Exports to China do not have a significant effect in either column. This indicates that the export channel of the China trade shock is not affecting the number of workers reallocating from employment in the traded sector to either employment in the nontraded sector or nonemployment. For both columns, most of the control variables are significant, with the exception of the percent employment in traded sectors in column (1). The percent employment that is female, high school educated, foreign born, and in routine jobs are all positive and significantly related to labor reallocation from the traded sector to the nontraded sector or nonemployment. In contrast, the average offshorability index negatively affects labor reallocation out of the traded sector. This indicates that microregions with higher shares of female employment, higher shares of skilled workers, higher shares of immigrants, and higher shares of workers in routine jobs experienced higher labor reallocation rates out of the traded sector. However, microregions with a higher average offshorability index experienced lower labor reallocation rates out of the traded sector. In contrast to our predictions, imports from China are reducing labor flows from the traded sector into nonemployment while exports do not have a significant effect.

Table 3.7 presents the results for the relationship between worker reallocation from nonemployment to employment in the formal sector and trade with China. We anticipate
### Table 3.7: Labor Reallocation from Nonemployment and Trade with China, 2008-2013

<table>
<thead>
<tr>
<th></th>
<th>(1) Nonemp. to Trade</th>
<th>(2) Nonemp. to Nontrade</th>
</tr>
</thead>
<tbody>
<tr>
<td>Δ Imports from China to Brazil per worker</td>
<td>-0.0002 (0.0002)</td>
<td>-0.0004*** (0.0001)</td>
</tr>
<tr>
<td>Δ Exports to China from Brazil per worker</td>
<td>-0.0001 (0.0001)</td>
<td>-0.0003 (0.0002)</td>
</tr>
<tr>
<td>Percent Employment Traded Sectors</td>
<td>-0.0078 (0.0116)</td>
<td>0.0070 (0.0075)</td>
</tr>
<tr>
<td>Percent Employment Female</td>
<td>0.0697*** (0.0220)</td>
<td>0.0505** (0.0204)</td>
</tr>
<tr>
<td>Percent Employment High School Educated</td>
<td>0.0350* (0.0181)</td>
<td>0.0569*** (0.0154)</td>
</tr>
<tr>
<td>Percent Employment Foreign Born</td>
<td>4.5654** (2.3124)</td>
<td>5.9718*** (2.1857)</td>
</tr>
<tr>
<td>Percent Employment Routine Jobs</td>
<td>0.0911*** (0.0231)</td>
<td>0.0597*** (0.0218)</td>
</tr>
<tr>
<td>Average Offshore Index</td>
<td>-1.9910* (1.0260)</td>
<td>-1.7348* (0.9408)</td>
</tr>
</tbody>
</table>

| Region | Yes | Yes |
| N      | 558 | 558 |
| $R^2$  | 0.6492 | 0.7248 |

**Notes:** Microregion level industry reallocation is calculated using the RAIS data for 2008 and 2013. An indicator variable is used to determine whether a worker was initially nonemployed (2008) and transitioned to employment in the formal sector (traded, nontraded, manufacturing, agricultural, or mining sector) in 2013. Microregion reallocation is calculated as the number of workers within a microregion who transitioned from nonemployment to the formal sector. All models also include a constant. Standard errors in parentheses are clustered at the state level. First stage estimates are similar to those in Table 3.4 and therefore are not included. * $p<0.10$, ** $p<0.05$, *** $p<0.01$

that imports from China will reduce reallocation into the formal sector while exports to China will increase reallocation into the formal sector. The results for reallocation into the traded sector are presented in column (1) and the results for reallocation into the
nontraded sector are presented in column (2). Beginning with column (1), we see that there is not a significant relationship between either imports from China or exports to China and reallocation into the traded sector. However, the results in column (2) indicate that imports from China reduce labor reallocation into the nontraded sector, but exports to China have an insignificant effect. This indicates that microregions more exposed to imports from China have a lower percentage of workers reallocate from nonemployment to employment in the nontraded sector. As previously mentioned, due to the mandated benefits afforded to workers in the formal sector and the working conditions in the informal sector, this type of reallocation is not beneficial to workers. The control variables in both columns continue to follow the patterns discussed for Table 3.6. The percent employment that is female, high school educated, foreign born, and in routine jobs are positive and significant while the average offshorability index is negative and significant.

Thus far, the analytical results for migration and labor reallocation somewhat support our hypothesis that imports from China will be associated with negative labor flows for workers while exports to China will be associated with positive labor flows for workers. Microregions more exposed to increased imports from China have lower migration rates than workers less exposed to imports from China. In contrast, microregions more exposed to increased exports to China have higher migration rates than microregions less exposed to exports. Together, this indicates that imports are deterring new workers while exports are attracting new workers. This is likely due to more employment opportunities associated with exports. Turning to labor reallocation, microregions with higher exposure to imports from China actually see lower labor reallocation out of the traded sector into either the nontraded sector or nonemployment. However, these microregions also experience lower labor reallocation out of nonemployment into the nontraded sector. We do not see any significant effect of Brazil’s exports to China on labor reallocation. While imports are associated with some negative and some positive labor flows for workers, exports are not significantly related to any industry labor flows thus far.
We now further break the analysis down by tracking labor reallocation out of nonemployment into three specific traded sectors, manufacturing, agriculture, and mining. We focus on these specific sectors due to the trade relationship between Brazil and China. Approximately 99% of imports from China are in the manufacturing sector, while approximately 40% of exports are in mining, 40% of exports are in agriculture, and about 15% of exports are in manufacturing. Therefore, we try to identify labor reallocation between nonemployment and the three traded sectors that are most heavily affected by trade with China. We anticipate that imports will increase the rate of reallocation into nonemployment while exports will decrease the rate of reallocation into nonemployment.

Table 3.8 presents the results for the impact of trade with China on labor reallocation from nonemployment to the manufacturing, mining, or agriculture sector in columns (1), (2), and (3), respectively. The results in column (1) show that neither imports nor exports affect labor reallocation from nonemployment into the manufacturing sector. The results in column (2) indicate that imports continue to have an insignificant effect on labor reallocation from nonemployment into the mining sector, but exports have a positive and significant effect on reallocation out of nonemployment into the mining sector. A microregion at the 75th percentile of import exposure experienced labor reallocation into the mining sector from nonemployment approximately 0.5 percentage points higher than a microregion at the 25th percentile. The relationship between exports to China and labor reallocation out of nonemployment into the mining sector represents positive labor flows from a worker’s perspective. The results in column (3) are similar to those in column (1); there is no significant relationship between trade with China and labor reallocation from nonemployment into the agriculture sector.

Last, we look at the relationship between trade with China and labor reallocation from the manufacturing, mining, or agriculture sector into nonemployment, seen in Table 3.9. These three labor flows represent the exact opposite flows presented in the

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15 The number of observations fluctuates across the three columns due to the fact that not all microregions experienced labor reallocation from nonemployment into the manufacturing, mining, or agriculture sector.
Table 3.8: Labor Reallocation from Nonemployment to Specific Sectors and Trade with China, 2008-2013

<table>
<thead>
<tr>
<th></th>
<th>Nonemployment to Manufacturing</th>
<th>Nonemployment to Mining</th>
<th>Nonemployment to Agriculture</th>
</tr>
</thead>
<tbody>
<tr>
<td>Δ Imports from China to Brazil per worker</td>
<td>0.0001 (0.0002)</td>
<td>-0.0002 (0.0003)</td>
<td>-0.0004 (0.0003)</td>
</tr>
<tr>
<td>Δ Exports to China from Brazil per worker</td>
<td>-0.0001 (0.0001)</td>
<td>0.0004*** (0.0001)</td>
<td>-0.0001 (0.0001)</td>
</tr>
<tr>
<td>Percent Employment Traded Sectors</td>
<td>0.0147 (0.0117)</td>
<td>-0.0385** (0.0171)</td>
<td>0.0105 (0.0077)</td>
</tr>
<tr>
<td>Percent Employment Female</td>
<td>0.0671*** (0.0188)</td>
<td>0.0255 (0.0228)</td>
<td>0.0275 (0.0333)</td>
</tr>
<tr>
<td>Percent Employment High School Educated</td>
<td>0.0087 (0.0183)</td>
<td>-0.0016 (0.0205)</td>
<td>-0.0041 (0.0133)</td>
</tr>
<tr>
<td>Percent Employment Foreign Born</td>
<td>3.0705 (2.0935)</td>
<td>1.5575 (2.2763)</td>
<td>0.6548 (1.6815)</td>
</tr>
<tr>
<td>Percent Employment Routine Jobs</td>
<td>0.0706*** (0.0204)</td>
<td>0.1171*** (0.0220)</td>
<td>0.0259 (0.0270)</td>
</tr>
<tr>
<td>Average Offshore Index</td>
<td>-1.0532 (0.8196)</td>
<td>0.0038 (1.1087)</td>
<td>-2.4375*** (0.5611)</td>
</tr>
<tr>
<td>Region</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>N</td>
<td>556</td>
<td>493</td>
<td>545</td>
</tr>
<tr>
<td>$R^2$</td>
<td>0.4854</td>
<td>0.2139</td>
<td>0.0818</td>
</tr>
</tbody>
</table>

Notes: Microregion level industry reallocation is calculated using the RAIS data for 2008 and 2013. An indicator variable is used to determine whether a worker was initially nonemployed (2008) and transitioned to employment in the formal sector (manufacturing, agricultural, or mining sector) in 2013. Microregion reallocation is calculated as the number of workers within a microregion who transitioned from nonemployment to each particular sector from 2008 to 2013. All models also include a constant. Standard errors in parentheses are clustered at the state level. First stage estimates are similar to those in Table 3.4 and therefore are not included. * p<0.10, ** p<0.05, *** p<0.01

previous table. We predict that import exposure will increase labor reallocation into nonemployment, particularly in the manufacturing sector, while exports will decrease labor
Table 3.9: Labor Reallocation from Specific Sectors to Nonemployment and Trade with China, 2008-2013

<table>
<thead>
<tr>
<th></th>
<th>(1) Manufacturing to Nonemployment</th>
<th>(2) Mining to Nonemployment</th>
<th>(3) Agriculture to Nonemployment</th>
</tr>
</thead>
<tbody>
<tr>
<td>Δ Imports from China to Brazil per worker</td>
<td>-0.0001 (0.0002)</td>
<td>-0.0007** (0.0003)</td>
<td>-0.0003 (0.0002)</td>
</tr>
<tr>
<td>Δ Exports to China from Brazil per worker</td>
<td>-0.0003 (0.0002)</td>
<td>0.0002*** (0.0001)</td>
<td>-0.0002 (0.0001)</td>
</tr>
<tr>
<td>Percent Employment Traded Sectors</td>
<td>0.0566*** (0.0078)</td>
<td>-0.0126 (0.0147)</td>
<td>0.0247** (0.0106)</td>
</tr>
<tr>
<td>Percent Employment Female</td>
<td>0.0318* (0.0168)</td>
<td>0.0184 (0.0190)</td>
<td>-0.0075 (0.0326)</td>
</tr>
<tr>
<td>Percent Employment High School Educated</td>
<td>0.0517*** (0.0160)</td>
<td>0.0227 (0.0152)</td>
<td>0.0105 (0.0158)</td>
</tr>
<tr>
<td>Percent Employment Foreign Born</td>
<td>5.1961** (2.2426)</td>
<td>3.4018* (1.7496)</td>
<td>0.0916 (2.0296)</td>
</tr>
<tr>
<td>Percent Employment Routine Jobs</td>
<td>0.0464** (0.0182)</td>
<td>0.1054*** (0.0145)</td>
<td>0.0233 (0.0285)</td>
</tr>
<tr>
<td>Average Offshore Index</td>
<td>-0.7765 (0.7763)</td>
<td>0.3004 (0.7868)</td>
<td>-1.8988*** (0.5917)</td>
</tr>
</tbody>
</table>

| Region | Yes | Yes | Yes |
| N | 554 | 472 | 549 |
| $R^2$ | 0.6784 | 0.5682 | 0.0845 |

Notes: Microregion level industry reallocation is calculated using the RAIS data for 2008 and 2013. An indicator variable is used to determine whether a worker was initially employed in the manufacturing, agriculture, or mining sector (2008) and transitioned to nonemployment in 2013. Microregion reallocation is calculated as the number of workers within a microregion who transitioned from each sector to nonemployment from 2008 to 2013. All models also include a constant. Standard errors in parentheses are clustered at the state level. First stage estimates are similar to those in Table 3.4 and therefore are not included. * p<0.10, ** p<0.05, *** p<0.01

Reallocation into nonemployment. The results in column (1), those for labor reallocation from the manufacturing sector into nonemployment, do not match our predictions. Trade
with China does not have a significant relationship with labor reallocation from employment in the manufacturing sector to nonemployment. The results in column (2) show that trade with China does significantly affect labor reallocation from employment in the mining sector to nonemployment. However, the results are the exact opposite of our predictions. Microregions more exposed to imports from China experienced lower reallocation rates from mining to nonemployment while microregions more exposed to exports to China experienced higher reallocation rates from mining to nonemployment. Thus, for the mining sector, imports are associated with labor flows beneficial to workers and exports are associated with labor flows harmful to workers. The results in column (3) are similar to those in column (1). Trade with China does not have a significant effect on labor reallocation flows from the agriculture sector into nonemployment.

The results for migration match our predictions while those for industry reallocation are quite different than our predictions. While imports are negatively associated with migration flows, exports are positively affecting migration flows. This suggests that exports are creating more labor market opportunities that attract new workers while imports are deterring new workers. Imports are also keeping workers employed in the traded sector (Table 3.6). Overall, exports to China do not have a significant effect on labor reallocation in Brazil, with the exception of reallocation from the mining sector to nonemployment and visa versa. Exports are associated with higher labor reallocation from mining into nonemployment, a negative transition for workers. However, exports are also associated with higher reallocation from nonemployment into mining, a positive transition. One possible explanation for these results is that employment in the mining sector is relatively volatile, independent of trade.

### 3.6 Conclusion

Despite recent pushback on trade openness policies, most countries continue to increase their reliance on international trade. As countries increase their trade with others,
they often become more specialized in the production of goods. In response to
specialization in certain industries, labor reallocates across different sectors of the economy. Additionally, since different sectors are concentrated in different geographic locations, specialization can also lead workers to migrate to regions with more labor market opportunities. In this paper, we explore the link between Brazil’s trade with China and labor reallocation within the country. We use UN Comtrade data and administrative panel data for the formal labor market in Brazil for the years 2008 to 2013. The RAIS data, a matched employer-employee data set, allows us to track workers across time to accurately measure labor reallocation rates across industries and migration rates across microregions.

The migration results confirm our predictions that exports will attract new workers, leading to higher migration rates, while imports will not attract new workers, leading to lower migration rates. We find that microregions more exposed to increased imports from China experienced migration rates approximately 0.5 percentage points lower on average. Additionally, microregions more exposed to increased exports to China experienced migration rates approximately 1.35 percentage points higher on average. These results suggest that areas with higher exposure to exports to China have more labor market opportunities, which attract new workers to the region. In contrast, areas with higher exposure to imports from China have fewer labor market opportunities, which does not attract new workers to the region. Our results for trade with China and migration contrast with previous results in the literature on the effect of trade on migration rates in Brazil. For example, Dix-Carneiro and Kovak (2017b) analyze migration in Brazil in the aftermath of Brazil’s trade liberalization episode, but do not find any significant effect of trade liberalization on migration.

In addition to migration, we also explore the relationship between trade with China and labor reallocation across industries within microregions. We analyze several different labor reallocation flows, but focus on transition into or out of nonemployment. Brazil, like many developing countries, has an extremely large informal sector. However, employment
in the formal sector provides workers with mandated benefits such as minimum wages, maximum work hours, and annual bonuses if a worker meets eligibility requirements. Additionally, employment in the informal sector is associated with longer hours, lower pay, and less safe working conditions (Cardoso, 2016). Therefore, we consider transitions out of nonemployment to be positive for workers and transitions into nonemployment to be negative for workers. In general, our results do not support our predictions that exports to China are associated with positive labor reallocation flows while imports from China are associated with negative labor flows. For example, microregions more exposed to imports from China experienced lower labor reallocation from the traded sector to nonemployment and from mining to nonemployment. We often did not find a significant relationship between exports to China and labor reallocation in Brazil. The two exceptions indicate that microregions more exposed to exports to China experienced higher flows from nonemployment to mining and higher flows from mining to nonemployment. Thus, the results were not consistently positive for workers.

Given the matched employer-employee nature of the RAIS data, we can accurately measure migration and labor market reallocation in Brazil. This is due to our ability to track workers over time, which is not possible with the majority of other data sets. Our results reveal the relationship between labor market dynamics and globalization and increased trade, specifically the China trade shock. From the worker perspective, exports are positively affecting migration, while imports are negatively affecting migration. However, the results for labor reallocation across industries and nonemployment do not provide a clear, consistent story. Our results highlight the importance for policymakers and economists to account for the effects of both trade flows on labor market outcomes. Only analyzing imports will likely overstate the negative effect of trade on workers while only analyzing exports will likely overstate the positive effect of trade on workers. Additionally, our results suggest that policies aimed at encouraging workers to relocate for employment opportunities could help workers displaced from trade.
3.7 Appendix

3.7.1 Supplementary Equations

We define a series of labor reallocation variables for each worker \( w \) in microregion \( i \) in year \( t \) as follows:

\[
migration_{wit} = \begin{cases} 
1 & \text{if emp. in microregion } i \text{ in } t \text{ & emp. in microregion } m \text{ in } t+1 \\
0, & \text{otherwise}
\end{cases}
\]

\[
trade_{to\_nontrade}_{wit} = \begin{cases} 
1 & \text{if emp. in traded sector in } t \text{ & in nontraded sector in } t+1 \\
0, & \text{otherwise}
\end{cases}
\]

\[
trade_{to\_nonemp}_{wit} = \begin{cases} 
1 & \text{if emp. in traded sector in } t \text{ & nonemp. in } t+1 \\
0, & \text{otherwise}
\end{cases}
\]

\[
nonemp_{to\_trade}_{wit} = \begin{cases} 
1 & \text{if nonemp. in } t \text{ & emp. in traded sector in } t+1 \\
0, & \text{otherwise}
\end{cases}
\]

\[
nonemp_{to\_nontrade}_{wit} = \begin{cases} 
1 & \text{if nonemp. in } t \text{ & emp. in nontraded sector in } t+1 \\
0, & \text{otherwise}
\end{cases}
\]
\[
\begin{align*}
\text{nonemp\_to\_manf}_{\text{wit}} &= \begin{cases} 
1 & \text{if nonemp. in } t \& \text{emp. in manf. sector in } t+1 \\
0 & \text{otherwise}
\end{cases}, \\
\text{nonemp\_to\_mining}_{\text{wit}} &= \begin{cases} 
1 & \text{if nonemp. in } t \& \text{emp. in mining sector in } t+1 \\
0 & \text{otherwise}
\end{cases}, \\
\text{nonemp\_to\_agric}_{\text{wit}} &= \begin{cases} 
1 & \text{if nonemp. in } t \& \text{emp. in agric. sector in } t+1 \\
0 & \text{otherwise}
\end{cases}, \\
\text{manf\_to\_nonemp}_{\text{wit}} &= \begin{cases} 
1 & \text{if emp. in manf. sector in } t \& \text{nonemp. in } t+1 \\
0 & \text{otherwise}
\end{cases}, \\
\text{mining\_to\_nonemp}_{\text{wit}} &= \begin{cases} 
1 & \text{if emp. in mining sector in } t \& \text{nonemp. in } t+1 \\
0 & \text{otherwise}
\end{cases}, \\
\text{agric\_to\_nonemp}_{\text{wit}} &= \begin{cases} 
1 & \text{if emp. in agric. sector in } t \& \text{nonemp. in } t+1 \\
0 & \text{otherwise}
\end{cases}.
\end{align*}
\]

For migration, we then calculate the percentage of workers within each microregion that migrated into the microregion from year \( t \) to year \( t+1 \). The share of workers who
migrated into microregion \( i \) from year \( t \) to \( t+1 \) is calculated as follows:

\[
micro\_migration_{it} = \sum_{w \in i} migration_{wit} \cdot \frac{micro\_emp_{it+1}}{micro\_emp_{it+1}};
\]

where \( migration_{wit} \) is previously defined and \( micro\_emp_{it+1} \) is the number of workers employed in microregion \( i \) in year \( t+1 \). We then calculate a series of variables at the microregion level that count the number of workers within a microregion \( i \) that reallocated from option A in 2008, year \( t \), to option B in 2013, \( t+1 \). For each microregion \( i \) in year \( t \) we calculate the following variables.

\[
micro\_trade\_to\_nontrade_{it} = \sum_{w \in i} trade\_to\_nontrade_{wit},
\]

where \( trade\_to\_nontrade_{wit} \) is previously defined.

\[
micro\_trade\_to\_nonemp_{it} = \sum_{w \in i} trade\_to\_nonemp_{wit},
\]

where \( trade\_to\_nonemp_{wit} \) is previously defined.

\[
micro\_nonemp\_to\_trade_{it} = \sum_{w \in i} nonemp\_to\_trade_{wit},
\]

where \( nonemp\_to\_trade_{wit} \) is previously defined.

\[
micro\_nonemp\_to\_nontrade_{it} = \sum_{w \in i} nonemp\_to\_nontrade_{wit},
\]

where \( nonemp\_to\_nontrade_{wit} \) is previously defined.

\[
micro\_nonemp\_to\_manf_{it} = \sum_{w \in i} nonemp\_to\_manf_{wit},
\]

where \( nonemp\_to\_manf_{wit} \) is previously defined.
$micro_{\text{nonemp\_to\_mining}}_{it} = \sum_{w \in i} nonemp_{\text{to\_mining}}_{wit}$,

where $nonemp_{\text{to\_mining}}_{wit}$ is previously defined.

$micro_{\text{nonemp\_to\_agric}}_{it} = \sum_{w \in i} nonemp_{\text{to\_agric}}_{wit}$,

where $nonemp_{\text{to\_agric}}_{wit}$ is previously defined.

$micro_{\text{manf\_to\_nonemp}}_{it} = \sum_{w \in i} manf_{\text{to\_nonemp}}_{wit}$,

where $manf_{\text{to\_nonemp}}_{wit}$ is previously defined.

$micro_{\text{mining\_to\_nonemp}}_{it} = \sum_{w \in i} mining_{\text{to\_nonemp}}_{wit}$,

where $mining_{\text{to\_nonemp}}_{wit}$ is previously defined.

$micro_{\text{agric\_to\_nonemp}}_{it} = \sum_{w \in i} agric_{\text{to\_nonemp}}_{wit}$,

where $agric_{\text{to\_nonemp}}_{wit}$ is previously defined.
REFERENCES


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APPENDIX

Figure 3.1: IRB Approval (a)

January 19, 2018

Peter Brummand, Ph.D.
Assistant Professor
Department of Economics Finance and Legal Studies
College of Commerce & Business Administration
The University of Alabama
Box 870224

Re: IRB # 17-OR-099-R1 “Who Creates Stable Jobs: Evidence from Brazil”

Dear Dr. Brummand:

The University of Alabama Institutional Review Board has granted approval for your renewal application. You have also been granted the requested waiver of informed consent. Your renewal application has been given expedited approval according to 45 CFR part 46. Approval has been given under expedited review category 7 as outlined below:

(7) Research on individual or group characteristics or behavior (including, but not limited to, research on perception, cognition, motivation, identity, language, communication, cultural beliefs or practices, and social behavior) or research employing survey, interview, oral history, focus group, program evaluation, human factors evaluation, or quality assurance methodologies.

Your application will expire on January 18, 2019. If your research will continue beyond this date, complete the relevant portions of Continuing Review and Closure Form. If you wish to modify the application, complete the Modification of an Approved Protocol Form. When the study closes, complete the appropriate portions of FORM: Continuing Review and Closure.

Should you need to submit any further correspondence regarding this proposal, please include the above application number.

Good luck with your research.

Sincerely,

[Signature]

Caribbean J. Myles, MSM, GMP, CIIP
Director & Research Compliance Officer
Office for Research Compliance
Figure 3.2: IRB Approval (b)

THE UNIVERSITY OF ALABAMA

Office of the Vice President for
Research & Economic Development
Office for Research Compliance

July 19, 2017

Peter Brummund, Ph.D.
Department of Economics
College of Commerce & Business Admin.
Box 87024


Dear Dr. Brummund:

The University of Alabama Institutional Review Board has granted approval for your proposed research.

Your application has been given expedited approval according to 45 CFR part 46. You have also been granted the requested waiver of informed consent. Approval has been given under expedited review category 7 as outlined below:

(7) Research on individual or group characteristics or behavior (including, but not limited to, research on perception, cognition, motivation, identity, language, communication, cultural beliefs or practices, and social behavior) or research employing survey, interview, oral history, focus group, program evaluation, human factors evaluation, or quality assurance methodologies.

Your application will expire on July 18, 2018. If your research will continue beyond this date, please complete the relevant portions of the IRB Renewal Application. If you wish to modify the application, please complete the Modification of an Approved Protocol form. Changes in this study cannot be initiated without IRB approval, except when necessary to eliminate apparent immediate hazards to participants. When the study closes, please complete the Request for Study Closure form.

Should you need to submit any further correspondence regarding this proposal, please include the above application number.

Good luck with your research.

Sincerely,

[Signature]

[Name]

Office for Research Compliance

{Footer information}