Abstract

Conventionally, it is believed that wages are primarily determined by aggregate demand for labour, treating its industrial composition as irrelevant. E.g., while trade liberalization affects aggregate labour demand and its industrial composition by differently impacting within-industry labour demands, it is deemed to affect wages mainly through the former rather than the latter. In principle, given that industries pay differently to similar workers, compositional shifts that favour high premium industries, increase the likelihood of high-paying employment and raise the value of outside options for unemployed workers within skill-groups. Consequently, wages strategically increase in all industries. Chapters 1 and 2 explore whether after controlling for changes in aggregate demand for labour, shifts in its industrial composition play an important role in determining wages.

Guided by the outcome of a general equilibrium model, exogenous, trade-induced variation in change in composition of local employment across cities in Mexico and Brazil during the 1990s is used to identify the associated causal wage effects, while controlling for changes in local demands for labour. It is found that shifts in industrial composition of local employment substantially impacts local sectoral wages.

Not much is known about the reasons behind differences in self-employment rate across space. While differences in local factors might matter, such factors are also impacted by changes in self-employment rate, making identification difficult. Chapter 3 asks to what extent local wages and wage-employment rate are important in determining local self-employment rate.

Building on the structure provided by a multi-city, multi-industry search and bargaining model of a labour market, the 1991 and 2000 waves of the Brazilian household census data are used to identify the long-term, causal effects of local employment rate and wages on local self-employment rate across Brazilian sub-national labour markets. Exogenous variation in local structures of wages and employment across Brazilian cities that were induced by trade liberalization of the 1990s in Brazil are used as the basis of the identification strategy. It is found that reallocation to self-employment from unemployment causally, and inversely, depends on local average wage and employment rate, and is substantially more responsive to changes in local wages.
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Dedication

Dedicated to my dear mother,

Layla Nazeri,

and to my precious friend and partner in life,

Rozita Jalili.
Chapter 1

Wage Effects of Shifts in Industrial Composition of Employment:
The Case of Mexican Cities and NAFTA, 1990-2000

1.1 Introduction

Conventionally, it is presumed that within any skill-group the wage is primarily determined by the aggregate demand for labour in the group rather than its industrial composition. The shifts in composition are deemed to only affect the accounting of a weighted average wage figure that uses employment shares of industries as weights (see Bound and Johnson, 1992). Measuring the average industrial wage in a local economy as local employment-share weighted sum of local industrial wages, such a presumption implies that shifts in employment shares do not affect wages. For instance, trade liberalization is deemed to affect wages primarily through its effect on demand for labour in different industries. This is while through differences in its impact across different industries, it also shifts the industrial compositions of labour demand, which has been ignored as a mechanism through which trade liberalization can impact wages.

Beaudry, Green, and Sand (2011) show how in a search and bargaining model of a labour market shifts in sectoral composition of employment favouring higher-paying industries can increase wages across all sectors. The intuition behind this model is straightforward. It is assumed that within a skill-group unemployed workers search for employment across all industries and find employment opportunities in any industry at a rate proportional to its employment share. Given that within any skill-group industries pay differently to identical workers, a shift in industrial composition that favours higher-paying industries increases the likelihood of employment in the high-premium industries within all skill groups, raises the value of outside option for unemployed workers in the skill-group and improves their bargaining position. Firms in all industries respond strategically and raise their wage offerings, resulting in sectoral wages to increase across all industries. As the model predicts, such general equilibrium (G.E.) inter-sectoral wage spillovers can be substantial. This mechanism opens a new way for looking into the wage effects of changes in trade policy and raises an interesting question: controlling for the wage effect of changes in demand for labour, are the wage effects of compositional shifts in labour demand economically important?
Building on the theoretical model in Beaudry et al. (2011), this paper uses the 1990 and 2000 waves of the Mexican household census data to study the long-term wage effects of shifts in composition of employment across Mexican local economies, referred to as cities hereinafter. Mexico joined the North American Free Trade Agreement (NAFTA) with Canada and the U.S. during the 1990s. This question is addressed here at the level of local labour market in Mexico during this decade, because exogenous, trade liberalization induced variations across these local labour markets – due to differences in exposure to the effects of change in trade policy – allow for proper identification of the relationship of interest.¹ Measuring local industrial composition as local employment-share weighted sum of national wage premia², the focus here is on estimating the wage effects of shifts in local industrial compositions of employment while controlling for the wage effects from changes in local employment rates.

Mexico of the 1990s is an interesting case study for this purpose. The macroeconomic, industrial, and trade policies of import-substitution era of the 1960s gave way to export-oriented policies of the 1970s and later to substantial liberalization of the economy in the late 1980s, which accelerated throughout the 1990s. Mexico entered the General Agreement on Tariffs and Trade (GATT) in August 1986 and in November 1993 signed onto NAFTA, which came into effect in January 1994.³ In addition to the comprehensive trade and investment liberalization of the 1980s and 1990s, in December 1994 as a result of a sudden devaluation of the Peso, Mexico

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¹ Too much spatial aggregation in analysis of changes in industrial composition can hide many important details. For example, formation of the maquiladoras as a result of industrial policies since the mid-1960’s combined with the trade liberalizations implemented by Mexico during the late 1980’s and throughout the 1990s, especially with the enactment of the North American Free Trade Agreement (NAFTA), resulted in disappearance of some manufacturing jobs from the U.S. that were being outsourced to Mexico. The outsourcing initially only impacted the border and northern regions within Mexico but over time, especially in the aftermath of NAFTA, spread out over the inner parts of the country as well. Figures (1.1) and (1.2) respectively illustrate the change in national and regional sectoral employment levels in Mexico during 1990-2000. While the aggregated national increase in Manufacturing employment represent the similar changes in Border, Northern, and Central regions, in the South the pattern is different. This is clearer in figure (1.3), where now the metropolitan area that includes Mexico City is dropped from the central region. Figure (1.4) and (1.5) respectively illustrate the change in national and regional sectoral employment shares during the 1990s. While the aggregated national change in Manufacturing employment represent the similar changes in Manufacturing, again in Manufacturing the pattern is very much different between the two; Manufacturing employment share declined at the aggregated national level but strongly increased in the Border region, mildly increased in the Northern area other than Border region, and decreased in the Central and Southern regions.

² These are regression adjusted wages or the part of wages that cannot be explained by attributes of worker or cities and can be associated with industries.

³ For more details see Ros (1994).
stepped into an economic crisis. Although recovering from it was relatively fast (Kose, Meredith, and Towe, 2004), Mexico nevertheless suffered from its impacts.\footnote{For more details see Edwards (1997).}

These happenings, especially the trade and investment liberalizations of the late 1980s and early 1990s, had major impacts on the structure of wages and employment in Mexico during the 1990s (among others see Aydemir & Borjas, 2007; Chiquiar, 2005; Chiquiar & Hanson, 2007; Hanson, 1998; Hanson, 2003; Hanson, 2005a; Hanson, 2005b; Jordaan, 2008; Richter, Taylor, and Yúnez-Naude, 2005; Tornell, Istermann, and Martinez, 2004). This literature, however, misses to consider the possibility of general equilibrium effect associated with shifts in industrial composition of employment. The findings here bring considerable evidence that the trade-induced changes in composition of employment across cities have had considerable impact on local wages.

Mexican census data is used to measure the compositions of industrial employment across cities. Geographical variation in this measure over time are then exploited to see whether local industrial wages vary systematically across cities with the changes in local compositions of employment, while controlling for the wage effects from changes in local employment rates. While in principle variations across cities in the change in local industry wages, employment rates, and composition of employments should allow for such a relationship to be identified, since in a general equilibrium setting these variables are related to each other, an identification strategy that isolates exogenous variations in the local industrial compositions and employment rates is devised. Trade liberalization in Mexico during the 1990s is seen as the source of such exogenous variations. In particular, the pre-trade local structures of employment and distances of each city from major commercial border crossings between Mexico and the U.S. are used to single out the exogenous variations in the two variables.

One source of endogeneity is the simultaneity that is present in a general equilibrium setting; the equilibrium levels of local employment shares and city-industry wages are simultaneously determined. Another source of endogeneity is improvements in unobserved advantages of high paying cities that may make such cities attractive for high-paying industries, resulting in the measure of industrial composition and sector-level wages to systematically move together. Also, a likely source of concern is that of a reflection problem (see Manski, 1993; Moffitt, 2001). In a search and bargaining framework, industrial wages act as strategic complements (see Beaudry et al., 2011), that is, high wages in one industry are associated with high wages in other industries.
and vice versa. This would make the measure of industrial composition endogenous. The identifications strategy used here addresses all these concerns.

Significant improvements in trade relations between Mexico and the U.S. in the aftermath of NAFTA justify the use of distance from Mexico-U.S. border as the basis of the IV strategy plausible. During the 1990s and as a result of NAFTA, the US became an ever more important trade partner for Mexico. The U.S. share in total international trade (export + import) of Mexico in all commodities increased from 68.2 percent in 1988 to 72 percent in 1990, 76.7 percent in 1994, and to 80.9 percent in year 2000. This is while, in 1999, 92.2% of the Mexico-U.S. trade by value passed through eight (of 22) commercial border crossings between Mexico and the U.S. Ground transportation using trucks is the main mode of transportation between the two countries as over the period of 1995-2000 the share of Truck transportation in total trade value by all modes averaged around 82 percent. Hence, the cost of transportation, and therefore distance from the U.S. border, can be a plausible candidate for understanding the extent to which the change in trade policy affected different cities and induced shifts in local sectoral compositions (in line with Hanson, 1998).

The findings here bring considerable evidence indicating that aside from the wage effects of shifts in city or city-industry level labour demands, the shifts in industrial compositions of local employment had sizable causal impacts on sectoral wages across Mexican cities. A shift in industrial composition of a city that increased its measure of industrial composition by one percentage point is found here to cause all industrial wages in the city to increase by about 3%, while controlling for the wage effects of changes in city or city-industry demand for labour. To the extent that the distances capture the effects of trade liberalization on within industry demands for labour across cities, 71% of the variation in the change in local compositions of employment, 26% of the variation in the change in local employment rates, and through these 19% of the variation in the change in local industrial wages across cities in Mexico are explained by the effects of trade liberalization.

5 2008 World Trade Data, Trade Analyser, Computing in the Humanities and Social Sciences (CHASS), University of Toronto, accessed via http://datacentre.chass.utoronto.ca/trade/ on September 21, 2009.
7 The change in logarithm of city-industry level wages has a mean of 0.082 across cities and a standard deviation of 0.252. The change in the measure of industrial composition has a mean of 0.033 across cities and a standard deviation of 0.022.
The instrumental variable (IV) estimations based on pre-trade structure of employment and proximity to Mexico-U.S. border confirm the findings from OLS estimates. The estimates here are shown to be robust to correcting for sample selection bias following the approach in Dahl (2002). Moreover, the findings are also shown to be robust in to introduction of alternative explanations in the literature for differences in wage changes across cities, such as those related to diversity of employment in a city (Glaeser, Kallal, Scheinkman, and Shleifer, 1992), levels of education (Acemoglu and Angrist, 1999; Moretti, 2004), and minimum wages (Fairris, Popli, and Zepeda, 2008).

Major changes in national trade or industrial policy are frequent in the less developed countries with already non-uniform distribution of economic development across regions. As shown here, such policy changes create geographic winners and losers depending on the distribution of effects across space. This is especially important if those who suffer were the historically poor regions in these countries. In Mexico, while shifts in local industrial compositions toward higher paying industries helped raise earnings of workers in most cities during the 1990s, in some cities mostly in South, due to reallocations away from high paying industries, the earnings declined or did not grow as fast. Given the large wage impacts found here, such patterns substantially contributed to worsening of the North-South wage gap in Mexico. These findings can explain the observed growing wag gap in Mexico (Hanson, 2005b; Chiquiar & Hanson, 2007). The importance of a spatially balanced economic development accentuate the need for policy-analysis approaches that take into account such general equilibrium effects and address spatial heterogeneity of policy impacts across regions and localities.

The paper is structured as follows. Section 1.2 briefly reviews the theoretical model and takes away a guideline that forms the empirical strategy discussed in section 1.3. Section 1.4 explains the data, section 1.5 reports the estimation results, and section 1.6 concludes.

### 1.2 Theory

In this section, the theoretical model in Beaudry et al. (2011) is briefly discussed. This model provides a structural relationship between the variables of interest based on which the empirical estimating equations are specified. The model shows how in a general equilibrium search and

---

8 See the appendix for in-detail reproduction of the model in Beaudry et al. (2011).
bargaining framework, aside from direct wage effects of changes in labour demand, a change in industrial composition of the demand affects sectoral wages. Essentially, when composition of employment in a city shifts toward higher paying sectors, the likelihood of finding a job that pays higher increases for all the unemployed workers. This improves their bargaining position when a match takes place and results in wages to rise in all sectors within the city. Whether this composition effect is economically important or not is an empirical question.

It is important to note that such wage effects are different from the direct city-industry or city level demand effects. In the event of a shift in sectoral composition of labour demand in a local economy, one would expect impacts on local wages within each city-industry as a result of the change in city-industry labour demand, or on local average wages as a result of the change in the overall city labour demand. However, the wage effects of shifts in industrial composition of labour demand discussed here are about the effects of within-industry changes in demand on other industries’ wages within a city; i.e., inter-industry wage effects of intra-industry changes in labour demand.

The economy is characterized by $C$ local economies (cities) in which firms produce goods and individuals seek employment over $I$ sectors. To produce and make profits, firms create new jobs and seek to fill the costly vacancies and weigh up the expected costs of keeping those vacancies against expected profits they make by employing workers and paying a wage that is city-sector specific. Each firm produces a sector specific product sold at a sector specific price. Similar to firms, individuals compare the expected benefits from being unemployed with accepting an employment offer at city-sector-specific wages. There is a random matching process through which workers are matched with firms. In steady-state equilibrium of this economy, the number of those matched is equal the death rate of matches and the value functions satisfy the standard Bellman relationship.

All throughout the model it is assumed that workers are not mobile across cities, an assumption that if relaxed is not going to change the key result because before migration between cities equalizes wages everywhere no matter what the industrial compositions are, increases in the cost of amenities within cities (for example price of housing) will bring migration to a halt. Furthermore, to avoid corner solutions in which all production concentrates in one city or in several cities but in one industry, it is as assumed that cities have different advantages in different sectors. These city-sector advantages are defined by exogenous distributions that determine each city’s advantages and disadvantages in all sectors in terms of
productivity and costs of creating vacancies within each sector. In equilibrium all the variables of the model, including city-industry wages and industries employment shares within a city, are functions of these exogenous city-sector advantage terms, which is a source of likely endogeneity later on when estimating the wage effects of shifts in composition of employment.

There is a final good, denoted $Y$, which is an aggregation of output from a total of $I$ sectors:

$$Y = \left[ \sum_{i=1}^{I} \left( a_i Z_i^X \right) \right]^{1/\chi}, \quad \chi < 1. \quad (1.1)$$

where differences in $a_i$ capture differences in demand across industries. The price of the final good is normalized to 1, while the price of the good produced in sector $i$ is given by $p_i$. The total quantity of each sectoral good produced at the national level ($Z_i$) is the sum of local productions of that good.

In city $c$ sector $i$, filling a vacancy generates a flow of profits for a firm given by:

$$p_i - w_{ic} + \epsilon_{ic}, \quad (1.2)$$

where $w_{ic}$ is city $c$ sector $i$’s specific wage, $\epsilon_{ic}$ is the city-sector specific cost advantage satisfying $\sum_c \epsilon_{ic} = 0$. Letting $V^f$ denote the discounted expected value of profits from a filled position and $V^v$ the discounted expected value of a vacancy, in steady state the value functions must satisfy the standard Bellman relationship:

$$\rho V_{ic}^f = (p_i - w_{ic} + \epsilon_{ic}) + \delta (V_{ic}^v - V_{ic}^f), \quad (1.3)$$

where $\rho$ is the discount rate and $\delta$ is the exogenous death rate of matches. The discounted expected value of profits from a vacant position must satisfy:

$$\rho V_{ic}^v = \phi_c (V_{ic}^f - V_{ic}^v), \quad (1.4)$$

where $\phi_c$ is the probability a firm fills a posted vacancy. Here, for simplicity and with no loss of generality, the periodical cost to maintain the vacancy is assumed to be zero.
The discounted expected value of being employed in sector \( i \) in city \( c \), denoted \( U_{ic}^e \), must as well satisfy the Bellman equation:

\[
\rho U_{ic}^e = w_{ic} + \delta(U_{ic}^u - U_{ic}^e), \quad (1.5)
\]

where \( U_{ic}^u \) represents the value associated with being unemployed when the worker’s previous job was in sector \( i \).

Representing the probability that an unemployed individual finds a job with \( \psi_c \) and the probability that an individual finding a job gets a random draw from jobs in all sectors (including sector \( i \)) – rather than being assigned a match in the previous sector – with \( 1 - \mu \), the value associated with being unemployed satisfies the Bellman relationship:

\[
\rho U_{ic}^u = b + \tau_c + \psi_c \left[ \mu U_{ic}^e + (1 - \mu) \sum_j (\eta_{jc} U_{jc}^e) - U_{ic}^u \right], \quad (1.6)
\]

where \( b \) is the utility flow of an unemployment benefit, \( \tau_c \) is a city specific amenity term, and \( \eta_{jc} \) represents the fraction of city \( c \)’s vacant jobs that are in sector \( j \). The key assumption for being able to solve the model explicitly is that workers can only search while being unemployed.

Once a match is made, workers and firms bargain a wage. Assuming that there are always gains from trade between workers and firms for all jobs created in equilibrium, the bargaining is set according to the following rule:

\[
(V_{ic}^f - V_{ic}^v) = (U_{ic}^e - U_{ic}^u). \quad (1.7)
\]

The probability a match is made is determined by the matching function:

\[
M((L_c - E_c), (N_c - E_c)), \quad (1.8)
\]

where \( L_c \) is the total number of workers in city \( c \), \( E_c \) is the number of employed workers (or matches) in city \( c \), and \( N_c = \sum_i N_{ic} \) is the number of jobs in city \( c \), with \( N_{ic} \) being the number of jobs in sector \( i \) in city \( c \). Given the exogenous death rate of matches, \( \delta \), and assuming a Cobb-Douglas form for the match function, the steady state condition is given by:
\[
\delta ER_c = M \left( (1 - ER_c), \left( \frac{N_c}{L_c} - ER_c \right) \right) = (1 - ER_c)^{\sigma} \left( \frac{N_c}{L_c} - ER_c \right)^{1-\sigma}, \quad (1.9)
\]

where \( ER_c \) is the employment rate. It follows that the proportion of filled jobs and vacant jobs in sector \( i \) can be expressed as \( \eta_{ic} = \frac{N_{ic}}{\sum_i N_{ic}} \).

The number of jobs created in sector \( i \) in city \( c \), \( N_{ic} \), is determined by the free entry condition:

\[
c_{ic} = V_{ic}^v, \quad (1.10)
\]

where \( c_{ic} \) is the cost of creating a marginal job and is necessarily increasing in the number of new jobs being created locally in that sector to have cities with employment across a wide range of sectors. Cities could also have a comparative advantage in creating certain types of jobs relative to others. Therefore, it is assumed that \( c_{ic} \) is a decreasing function of the city-sector specific measure of advantage denoted \( \Omega_{ic} \):

\[
c_{ic} = \frac{N_{ic}}{Y_i + \Omega_{ic}}. \quad (1.11)
\]

where \( Y_i \) reflects any systematic differences in cost of entry across sectors, which allows to assume that \( \sum_c \Omega_{ic} = 0 \).

Finally, the probability an unemployed worker finds a match and the probability a firm fills a vacancy respectively satisfy:

\[
\psi_c = \frac{\delta ER_c}{1 - ER_c} \quad \text{and} \quad \phi_c = \left( \frac{1 - ER_c}{\delta ER_c} \right)^{\frac{\sigma}{1-\sigma}}. \quad (1.12)
\]

A steady state equilibrium in which the price of sectoral output is taken as given, consists of value of \( N_{ic}, w_{ic} \), and \( ER_c \) that satisfy equations (1.7), (1.9), and (1.10). These equilibrium values will depend on (among other things) the city specific productivity parameters \( \Omega_{ic} \) and \( \epsilon_{ic} \). An equilibrium for the entire economy has the additional requirement that the prices for sectoral goods must ensure that markets for these goods clear.
Solving the model for city-sector wages gives the following relationship:

\[ w_{ic} = \gamma_{c0} + \gamma_{c1}p_i + \gamma_{c2} \sum_j \eta_{jc} w_{jc} + \gamma_{c1}e_{ic}, \]  

(1.10)

where the coefficients are implicit functions of the employment rate through \( \psi_c \) and \( \phi_c \).

The parameters in this equation are implicit functions of city-sector employment shares, city level employment ratios, the extent of mobility of labour across sectors, and exogenous city-sector performance advantage terms.

The derived equation for city-sector wages captures the notion that in a search and matching framework, sectoral wages act as strategic complements; that is, high wages in one sector are associated with high wages in other sectors.\(^9\) According to equation (1.10), an increase in wage in one sector in a city increases the average wage and consequently all wages in all sectors in the city. This makes impossible to estimate \( \gamma_{c2} \), the coefficient of city average wage. The strength of the strategic complementarity is captured by \( \gamma_{c2} \), which is implicitly a function of mobility of workers across sectors. If workers are immobile across sectors, \( \gamma_{c2} \) becomes zero, this effect disappears, and wages are determined solely by the value of marginal product.

According to equation (1.10), a pure shift in sectoral composition of employment that causes a one unit increase in the average city wage, \( \sum_j \eta_{jc} w_{jc} \), increases all sector-level wages in average by \( \gamma_{c2} \) in the city. But these increases in all city-sector wages cause the average wage to increase by another \( \gamma_{c2} \) units, generating a further round of adjustments. By the time the new steady state is established, the total effect of the pure change in sectoral composition on the average wage would therefore be\(^ {11} \) \( \frac{1}{1-\gamma_{c2}} \), if \( \gamma_{c2} \) is smaller than one can be shown is the case here.

To deal with the reflection problem, and to directly show the impact of employment rate, manipulation\(^ {10}\) of this equation results in the following equation:

---

\(^9\) For more details on the classic reflection or social interaction problem see Manski (1993) and Moffitt (2001).
\(^ {10}\) To get equation (1.11), one should take a linear approximation of equation (1.10) at identical composition of employment across cities (\( \eta_{ic} = \eta_i = 1/I \)) and equal employment rates (\( ER_c = ER \)), which arises when there is no differences in city-sector advantages across cities, and assume that matching probabilities across cities and sectors are all the same, so that all the \( \gamma \) coefficients become nothing but the averages across cities at these similar matching probabilities.
\[ w_{ic} = d_i + \frac{\gamma_2}{(1 - \gamma_2)} \sum_j \eta_{cj}(w_j - w_1) + \gamma_{i5}ER_c + \xi_{ic}, \quad (1.11) \]

where \( d_i \) is a sector specific effect that can be captured in an empirical specification by including sector dummies, \( w_j - w_1 \) is the national level wage premium\(^{11} \) in sector \( j \) relative to sector 1, \( ER_c \) is the city level employment rate and the added coefficient, \( \gamma_{i5} \), reflects the effect of a change in the employment rate within a sector on wage determination in that sector. This coefficient may vary across sectors since the bargaining power of firms could depend on the tightness of labour market within each industry.

Equation (1.11) shows how city-sector wages depend on the industrial composition of a city’s employments, captured by the term \( \sum_j \eta_{cj}(w_j - w_1) \). This term is denoted hereinafter by \( R_c \) and is referred to it as the measure of industrial composition\(^{12} \):

\[ R_c = \sum_j \eta_{cj}(w_j - w_1). \quad (1.12) \]

Differencing the structural equation in (1.11) within a city-sector cell across two steady state equilibria, gives the following estimating equation:

\[ \Delta w_{ic} = \Delta d_i + \frac{\gamma_2}{(1 - \gamma_2)} \Delta R_c + \gamma_{i5} \Delta ER_c + \Delta \xi_{ic}, \quad (1.13) \]

where \( \Delta d_i \) is a sector specific effect that can be captured in an empirical specification by including sector dummies, and \( \Delta \xi_{ic} = \gamma_1 \Delta \epsilon_{ic} + \frac{\gamma_2}{(1 - \gamma_2)} \sum_j \frac{1}{I} \Delta \epsilon_{jc} \) is the error term with \( I \) being the total number of sectors.

The focus of the current study is on estimating the coefficient on the change in measure of industrial composition in (1.13); \( \frac{\gamma_2}{(1 - \gamma_2)} \). Consistent estimates of this coefficient would shed light

\(^{11}\) Note that the theory is silent about attributes of workers, and specifically their skills. One should think of the wages and wage premia as calculated for one skill group so that an increase in the measure of industrial composition is not an increase of skill. In the empirics these will be obtained controlling for skills and other attributes of the workers.

\(^{12}\) Notice that a high value for the measure of industrial composition indicates that the city’s employment is concentrated in higher paying sectors.
on the extent of city-level strategic complementarity between wages in different sectors by backing out $\gamma_2$. But the coefficient $\frac{\gamma_2}{(1-\gamma_2)}$ is of interest in its own right as it provides an estimate of the general equilibrium effect of a one unit increase in the measure of industrial composition on within sector wages, as opposed to $\gamma_2$, which provides the partial unidirectional effect.\(^{13}\)

Examining wages in one sector in different cities, a positive value for $\frac{\gamma_2}{(1-\gamma_2)}$ implies that for example agriculture wages will be higher in cities where employment is more heavily weighted toward high rent sectors, where high rent sectors are defined in terms of national level wage premia. This arises in the model because the unemployed workers in the Agriculture sector have better outside options in cities with higher share of their employment in high-rent industries.

Equation (1.13) will be used as the specification for the empirical analysis of the wage effects of shifts in industrial composition of employment. However, endogeneity of the variables in this equation puts the success of the OLS estimates in danger. As explained before, one source of endogeneity here is the kind of unobserved city-wide improvements that cannot be controlled for in the estimating equations but may systematically move the measure of industrial composition and wages together. The success of the estimation strategy relies upon the properties of the error term in (1.13). In so far as the change in measure of industrial composition is concerned, the requirement for OLS to give consistent estimates of the coefficients in (1.13) is as follows:

$$\text{plim}_{C,I \to \infty} \frac{\Delta R_c \Delta \xi_{ic}}{I C} = \text{plim}_{C,I \to \infty} \frac{\Delta R_c \sum_{i=1}^{I} \sum_{c=1}^{C} \Delta \xi_{ic}}{I C} = 0,$$  \quad (1.14)$$

recognizing that a similar condition is required for the change in employment rate. As shown in the appendix, since the error term is $\Delta \xi_{ic} = \gamma_1 \Delta \epsilon_{ic} + \gamma_1 \frac{\gamma_2}{(1-\gamma_2)} \sum_{j} \frac{1}{I} \Delta \epsilon_{jc}$, this condition effectively reduces to the properties of $\epsilon_{ic}$, the city-industry productivity advantage terms. Both the measure of industrial composition and employment rates may be endogenous because they are functions of $\eta_{ic}$’s, which are correlated with the $\epsilon$’s. Intuitively, for (1.15) to be satisfied the error terms, averaged across industries within cities, should be independent of both past and

\(^{13}\) $\gamma_{2c}$ is a measure of the extent of strategic complementarity across industries within a city according to equation (1.10), which gave rise to the total $\frac{1}{(1-\gamma_2)} (= 1 + \frac{\gamma_{2c}}{1-\gamma_{2c}})$ increase in average wages after a shift in industrial composition that directly increase the average in the equation by one unit. $\gamma_2$ is the average of $\gamma_{2c}$ across cities with $\frac{\gamma_2}{1-\gamma_2}$ being the general equilibrium wage effects of the initial shift in the industrial composition of employment.
present structures of employment in all cities.\footnote{These assumptions are discussed in the appendix in detail.} While independence from past may be plausible, contemporaneous independence is considered stringent. Also, it is important to note that since the parameters in (1.13) are identified off of variation in the variables of the model across cities, the industrial wage premia in the measure of industrial composition are not a source of endogeneity as they vary across industries and not cities. In other words, in principle, to identify the coefficients in (1.13), data on one industry across cities should suffice.

Since both of these assumptions together may not hold in the data, an instrumental approach is devised here that can consistently estimate the parameters in (1.13) under a less stringent assumption. Essentially, as shown in the appendix, if the $\epsilon$’s are assumed to follow a random walk process with increments that are independent of the past and the proximity of cities to the Mexico-U.S. border, the variations across cities in the change in local employment rate and composition of employment that are correlated with the measures of distance can be used to identify the coefficients in (1.13).

Given that the data used in this study covers the years 1990 and 2000 and that the change in trade policy in Mexico occurred in the middle of this period, independence from past is considered plausible here. Moreover, it is expected that industrial wage structure in cities to be related to distance from the northern border only through the induced changes in the overall demand and its composition, that are already controlled for in equation (1.13).

Thus, for example, a useful instrumental variable could be a suitable function of the initial period local employment shares and distances from border, that varies across cities and is highly correlated with the change in the measure of industrial composition across cities. The decomposition of changes in the measure of industrial compositions into two parts, one based on changes employment shares and the other based on changes in national wage premia, will be used as a guide in choosing the suitable functional form in generating the instruments\footnote{\[\Delta R_c = \Delta \sum_j \eta_{c_j} \cdot (w_j - w_1) = \sum_j \Delta \eta_{c_j} \cdot (w_j - w_1) + \sum_j \eta_{c_j} \Delta (w_j - w_1) = \Delta \sum \eta + \Delta \sum \eta \Delta w\]} . Section 1.3 presents a more detailed exposition of generating the instruments and provides a detailed discussion of the source of the endogeneity and the assumptions required for the OLS or IV approach to work.
1.3 Empirical Strategy

The aim of this section is to explain the empirical strategy, potential issues, and necessary steps and approaches devised for a proper identification of the relationship between the measure of industrial composition and city-sector wages. Briefly, the empirical strategy here is to explore geographical variation in the change in industrial composition to see whether it is systematically related to the change in city-sector wages across cities, while the effect from changes in local employment rates are controlled for. Several preliminary steps are required to prepare the data for estimating the ultimate relationship of interest. Also, sample selection bias and endogeneity are potential issues that may jeopardize the success of the OLS estimation strategy. This section explains the preliminary steps and addresses several estimation issues.

The empirical estimating equation that closely matches equation (1.13) is specified as:

$$\Delta w_{ci} = \alpha + d_i + \beta \Delta R_c + \gamma_i \Delta ER_c + \Delta \xi_{ci}.$$  

(1.15)

where $\Delta$ indicates time difference over two distinct points (years 1990 and 2000) in time ten years apart from each other, for which the data is available. $d_i$ indicates a full set of sector dummies excluding the base sector. The left hand side variable is the change wages specific to sector $i$ in city $c$, $\Delta R_c$ is the change in industrial composition of employment in city $c$, and $\Delta ER_c$ is the change in city-industry employment rate in city $c$, where city employment rate is defined as the proportion of employed workers out of working age population in city $c$. $\Delta \xi_{ci}$ is the error term. $\Delta ER_{c1}$ can also be replaced by $\Delta ER_c$ to account for the wage effects of changes in the city-level labour demand.

The parameter of interest is $\beta$ that captures the relationship between the measure of industrial composition and city-sector wages, while controlling for the impact of changes in the city or city-sector labour demand. In other words, in this specification the relationship captured by the estimates of $\beta$ is in isolation from the wage effects induced by changes in the demand for labour. $\beta$ captures the magnitude of the total G.E. effects of a shift in industrial composition on the average wage. It essentially indicates how many times such G.E. effects are larger than the pure shift-share accounting of the effect on average wage of a shift in composition of employment that changes the measure of industrial composition by one unit while keeping wages constant.

In estimation of equation (1.15) and conducting inferences, consistency of the estimates is crucial. Assuming consistent estimation, the goal would be to test the null hypothesis that $\beta = 0$. 
If the null cannot be rejected, the inter-sectoral wage interactions in the process of wage determination in local economies can be disregarded. On the other hand, however, a statistically significant and positive coefficient is indicative of a general equilibrium mechanism through which local sectoral composition of employment in average has a significant impact on city-industry wages across all cities. If this mechanism is estimated to be sizable, disregarding the general equilibrium impact on wages could turn out to be costly in developmental policy making and a proper evaluation of trade of industrial policy changes that often bring about major changes in the composition of employment.

In equation (1.15) the measure of industrial composition is computed as the weighted sum of national sectoral wage premia, using city-industry employment shares as the weights:

$$R_{ct} = \sum_{i} \frac{e_{cit}}{\sum_{i} e_{cit}} \cdot \left(\frac{w_{it}}{w_{1t}} - 1\right), \quad (1.16)$$

where $e_{cit}$ indicates employment in sector $i$, city $c$, in year $t$, $w_{it}$ indicates sector $i$’s specific wage at the national level in year $t$, and in the same way $w_{1t}$ measures the intrinsic wage in sector one at the national level. In equation (1.16), $\frac{e_{cit}}{\sum_{i} e_{cit}}$ or the share of sector $i$ in total employment in city $c$ is the weight associated with the national wage premium in sector $i$, indicated by $\left(\frac{w_{it}}{w_{1t}} - 1\right)$. Note that the wage premium is expressed in percentages. So, the measure of industrial composition is measures how much wage premium a city generates based on its composition of employment across different sectors, given the premium that each industry generates at the national level. A shift in the composition of employment favouring high-rent industries will increase this measure. At the same time, a change in the national industry wage premia in favour of the high-share industry also increases this measure. From the viewpoint of the theory, such changes in the wage premia at constant composition of employment should impact city-industry wages in the same way as a shift in the composition of employment favouring high-rent industries at constant wage premia does, as both increase the value of an expected future employment.

Notice that as a result of measuring industrial composition using national wage premia, a city with relatively higher wages in all sectors is not necessarily going to have a higher measure of industrial composition, by construction. If the spillover mechanism from good jobs is at work,
then, it is expected to see higher wages across all sectors in cities with higher measures of industrial composition.

If there are city wide improvements that systematically move the measure of industrial composition and wages together, the OLS estimates are no more reliable. This is the intuitive interpretation of the identification assumption in equation (1.14) that is required for the consistency of the OLS estimates. To make sure of consistency of the OLS estimates, an IV approach will be devised to deal with the likely endogeneity of the regressors.

The city-sectoral employment shares, \( \frac{e_{cit}}{\sum_i e_{cit}} \)'s, can directly be calculated from the individual level data using appropriate sampling weights for aggregation. The industry specific wage premia are estimated from the individual data using the following specification estimated separately for each year:

\[
\ln(W_{kc}) = \varphi + \varphi_c d_c + X_k' \gamma + \sum_i \omega_i d_i + \epsilon_{kcit},
\]

where \( W_{kc} \) is the wage received by person \( k \) in city \( c \) working in sector \( i \), \( X_k \) denotes an array of the worker’s attributes, \( d_i \) and \( d_c \) indicate sector and city dummies, and \( \ln(.) \) is the natural logarithm function. In equation (1.17), estimates of \( \omega_i \)'s in each year by definition capture the national level sectoral wage premia relative to the base sector and can be used to replace the term \( \left( \frac{w_{it}}{w_{1t}} - 1 \right) \) in equation (1.16):

\[
R_{ct} = \sum_i e_{cit} \cdot \left( \frac{w_{it}}{w_{1t}} - 1 \right) = \sum_i e_{cit} \cdot \omega_{it}.
\]

The next variable that requires attention is the left-hand-side variable in equation (1.15), \( w_{cit} \). In the theoretical model, the worker is abstracted from all its attributes in the sense that the wages considered in the model are independent of the attributes of the workers and are intrinsic to the sector and city where they work.\(^{16}\) It is therefore necessary to adjust the data on individual wages for all the attributes for which information is available and properly aggregate the wages from individuals to the city-sector level. The coefficients of city-sector dummies in the following

\(^{16}\) Another way to interpret this, is to say that the model is for a person with given skill level.
estimating equation can be considered as regression-adjusted wages for the attributes of workers averaged across individuals within each city-sector cell:

\[ \ln(W_{kci}) = X_k'\gamma + \sum_c \sum_l w_{cl}d_{ci} + \omega_{kci}. \]  

(1.19)

Equation (1.19) can be estimated separately for each year using the sampling weights in the data so that each round of estimation generates the appropriately aggregated city-sector wages for that year.

In the same way as city-sector employment shares, the city level employment rates can also be computed directly from the data using the sampling weights. Having generated all the appropriate dependent and explanatory variables, equation (1.15) can be estimated to see whether changes in sectoral composition of employment in Mexican cities systematically relay externalities on all local sector-level wages. Before moving on the estimation, it only remains to address the concerns about endogeneity and sample selection, as follows.

1.3.1 Selection

In this section the concern about sample selection bias that the empirical strategy may suffer from is addressed. If workers are mobile across cities and choose where to live and work by comparing different cities in terms of their personal priorities, then individuals currently observed living in a city are not a random sample of the population. An individual’s wage is not observed in any city other than the one they choose to be a resident of at the time of census. This will compromise the conditions of zero mean error terms, required for the consistency of OLS estimates in estimation of industry specific wage premia and city-industry wages. In practice, in equations (1.17) and (1.19) this issue is in fact relevant in a conditional mean term; i.e., zero mean error conditioned on the wage figure being observed. Taking conditional expectations from equation (1.17) gives:

\[ E[\ln(W_{kci})|X_k, d_i, and W_{kci} being observed] = \alpha + X_k'\gamma + \sum_i \alpha_i d_i + E[\varepsilon_{kci}|X_k, d_i, and W_{kci} being observed], \]  

(1.20)
where it is not clear if the conditional error mean term is actually zero in a sample suffering from self selection. If this is not the case, then the conditional residual mean term is correlated with other regressors and OLS is no more consistent.

Intuitively, if suddenly a group of individuals move from a city to another city in expectation of higher wages for reasons not observable but related to the structure of wages ($Δ\xi_{i,c}$), the change in the measure of industrial composition in equation (1.15) will also capture the impact of this sort of movements and the OLS estimation of this equation may give significantly-different-from-zero estimates of the relationship of interest without it really existing. Thus, it is very important to adjust the empirical strategy to correct for this possibility, which is carried out by implementing the approach in Dahl (2002).

Dahl (2002) develops an econometric approach to correct for sample selection bias in addressing why high rate of interstate migration has not led to equalization of returns to schooling across different states in the U.S. He develops a multi-market model of mobility and earnings in which individuals choose where in any of the 50 U.S. states to live and work, and proposes a semi parametric methodology to correct for sample selection bias in such a choice model. He shows that the bias correction is an unknown function of a small number of selection probabilities, which are calculated without making any distributional assumptions, simply by classifying similar individuals into cells and estimating the proportion of movers and stayers for each place of birth and cell combination. His work essentially shows that in order to correct for the selection bias, under some sufficiency conditions, the conditional error mean term in (1.20) can be replaced by an unknown function of the relevant migration probabilities in the outcome regression, which can then be estimated with a simple OLS. Modifying Dahl’s approach to current setting, the mean error term can be identified as a function of relevant migration probabilities:

$$E[\varepsilon_{kcl}|X_k, d_i, and W_{kcl} being observed] = \sum_b d_{kbc} \cdot f_{bc}(P_{kbc}, P_{kbb}) + \vartheta_{kci}, \quad (1.21)$$

where $d_{kbc}$ is an indicator that takes one only if person $k$ born in state $b$ has actually moved to city $c$, $E[\vartheta_{kcl}|X_{kci}, d_i, and W_{kcl} being observed] = 0$, and $f_{bc}(\cdot)$ is an unknown function of the probabilities that person $k$, born in state $b$, is observed in city $c$ ($P_{kbc}$) and that person $k$, born
in state \( b \), remains in the same state \( (P_{kb}) \). The function \( f_{bc}(\cdot) \) is chosen here to be quadratic in each of the probabilities separately. In this way, equation (1.17) can be written as:

\[
\ln(W_{kci}) = \alpha + X_k'y + \sum_i \omega_i d_i + \sum_b d_{kbc} \cdot f_{bc}(P_{kb}, P_{kbb}) + \theta_{kci} \quad (1.22)
\]

Notice that for non-movers, the correction terms are only functions of the probability of staying since for individuals who do not move from their state of birth \( c = b \).

Similarly, equation (1.19) can also be corrected for selection bias:

\[
\ln(W_{kci}) = \alpha + X_k'y + \sum_c \sum_i w_{ci} d_{ci} + \sum_b d_{kbc} \cdot f_{bc}(P_{kb}, P_{kbb}) + \zeta_{kci}, \quad (1.23)
\]

where \( E[\zeta_{kci}|X_k, \text{ and } W_{kci} \text{ being observed}] = 0 \).

In a given city \( c \), the identification for the movers \( (P_{kb}) \) comes from the variation in the state of birth and, likely, the distance between the state of birth and the city which determines the probability that people make a given move. So, here the underlying assumption is that the state of birth and the distance between the state of birth and the city the person is observed in for the case of movers are not directly related to the wage a person receives. In other words, two individuals with exactly similar characteristics, living and working in the same city, but born in different states with different distances from this city, will not necessarily receive different amounts. For the stayers, however, identification comes from the differences in family status and hence is the assumption that family status is not directly related to the wage the person receives.

### 1.3.2 Endogeneity

Both the measure of industrial composition and employment rate are likely to be endogenous in a general equilibrium framework. As was indicated before and is reviewed in detail in the appendix, as far as the change in the measure of industrial composition is concerned the consistency of estimates of the parameters in equation (1.15) relies partly\(^{17}\) on the following condition:

\(^{17}\) A similar condition is required for the employment rate, \( \Delta ER_c \).
\[
\lim_{C,I \to \infty} \frac{1}{C} \sum_{l=1}^{I} \sum_{c=1}^{C} \Delta R_c \Delta \xi_{ic} = \lim_{C,I \to \infty} \frac{1}{I} \sum_{c=1}^{C} \sum_{i=1}^{I} \Delta \xi_{ic} = 0, \quad (1.24)
\]

where from the theoretical part \( \Delta \xi_{ic} = \gamma_1 \Delta \epsilon_{ic} + \gamma_1 \frac{\gamma_2}{1-\gamma_2} \sum_j \frac{1}{I} \Delta \epsilon_{jc} \). City-sector performance advantage terms can always be decomposed as \( \epsilon_{ic} = \hat{\epsilon}_c + v_{ic}^{\epsilon} \) into a common city advantage, \( \hat{\epsilon}_c \), and relative city-sector advantage term, \( v_{ic}^{\epsilon} \), where by construction \( \sum_i v_{ic}^{\epsilon} = 0 \). Therefore, the condition above depends primarily on properties of the absolute advantage component \( \hat{\epsilon}_c \), as \( v_{ic}^{\epsilon} \) drops out of the average of the error term across cities in the condition above. It can be shown (see the appendix) that the condition for consistency of OLS estimates relies on the assumption that the common city-level advantages are independent of past and present relative advantages – that are implicitly present in the employment shares used in the measure of industrial composition. Intuitively, this requirement means that shifts in the measure of industrial composition should not depend on average city-wide improvements in wages in that city. In other words, it implies that whatever drives general city performance is not related to a particular pattern of industrial structure. Since these conditions, especially the contemporaneous independence, seem to be too stringent and both of these conditions may not hold at the same time in the data, use of instrumental variables is necessary to be able to consistently estimate equation (1.15).

Under a weaker assumption that common city advantages are independent of the pre-trade set of relative advantage factors and proximity to Mexico-U.S. border, an instrumental variable approach is devised. For these conditions to be satisfied, it is sufficient if common city advantages follow a random walk process with increments independent of past values and distance from border.

It is hypothesized here that the trade-induced variations in the change in employment share of each industry across cities, depending on their distance from major commercial border crossings between Mexico and the U.S., can be used as the basis for identification. Essentially, the trade induced changes in industry employment shares in each city is predicted using pre-trade structure of employment and the distances of that city from eight major commercial Mexico-U.S. border crossings. These are then used to create instruments for the regressors in equation (1.15). Validity of this group of instruments relies as well on the assumption that the city common
advantage terms follow a random walk process with increments independent of past and the proximity to the Mexico-U.S. border.

By using distance from border, to the extent that this is a valid and relevant approach in identifying the trade-induced variation in structure of employment across cities (see Hanson, 1998), the IV estimates capture the trade-induced effects of changes in industrial composition on city-industry wages. While the validity of the instruments cannot be tested, their relevancy can be tested by the performance of the instruments in the first-stage regressions of the IV approach.

To what extent is the assumption required for validity of distance-based instruments reasonable? Briefly, as long as changes in employment rate and industrial composition are controlled for, distances from border do not seem to belong to equation (1.15) as determinant of city-industry wages. In general, time invariant geographic attributes of a city such as its distance from U.S. border are not expected to be part of the wage determination process in different cities. In other words two cities with different distances from border do not necessarily have different wage structures or wage growth trajectories. However, one may think possible that, because trade liberalization falls in the middle of the period being studied here, distance from border may have become relevant in the wage determination process in across cities. While being close to the capital city or other major cities was an advantage in the pre-NAFTA era, in its aftermath being close to the border might have become an advantage (or a disadvantage). Hence, is the identification assumption mentioned above. Nevertheless, as far as the wage determination process is concerned, what is conceived as advantage in cities closer to or farther from the border is because of the distributive labour demand and supply effects of trade with the U.S. across different cities, which should affect the wage determination process through changes in demand for labour in cities and sectors or the supply of labour. Labour demand effects of trade on wages are relayed through the trade-induced changes employment rate and industrial composition, both of which are controlled for in equation (1.15), or through increase in migrants in search of work that were corrected for through correction of sample selection bias. In other words, if there is a relationship between distance from border and changes in city-sectoral wages, it should be through mechanisms that are already controlled for in IV estimation of equation (1.15).

To what extent are distances from border relevant? In short, in the aftermath of NAFTA, the U.S. became an ever more important trade partner for Mexico. With the surface transportation as the main mode of transportation between the U.S. and Mexico, distance of Mexican cities from
the U.S. border seems relevant in figuring out the extent of exposure to foreign competition or
foreign direct investment to understand the distributive impacts of U.S.-Mexico trade across
different cities within Mexico. Share of the US in total (export + import) international trade of
Mexico in all commodities increased from 68.2 percent in 1988 to 72 percent in 1990, 76.7
percent in 1994, and to 80.9 percent in year 2000. \(^{18}\) This is while over the period of 1995-2000,
the share of Truck transportation in total trade value by all modes of transportation averaged
around 82 percent \(^{19}\), indicating that the cost of transportation and hence the distance from US
border, is a likely relevant candidate for understanding how changes in trade policy could have
affected different cities and sectors differently across Mexico.

The instruments are constructed based on the decomposition of \(\Delta R_{ct}\) into a part that captures
the change in the measure of industrial composition resulting from changes in employment
shares (\(\Delta R_{ct}^{\Delta \eta}\) below) and another that captures the changes resulting from variations in national
level wage premia of sectors (\(\Delta R_{ct}^{\Delta w}\) below):

\[
\Delta R_{ct} = \sum_i \eta_{cit} \sigma_{it} - \sum_i \eta_{cit-1} \sigma_{it-1} \\
= \sum_i \eta_{cit} \sigma_{it} - \sum_i \eta_{cit} \sigma_{it-1} + \sum_i \eta_{cit} \sigma_{it-1} - \sum_i \eta_{cit-1} \sigma_{it-1} \\
= \sum_i (\eta_{cit} - \eta_{cit-1}) \sigma_{it-1} + \sum_i \eta_{cit}(\sigma_{it} - \sigma_{it-1}) = \Delta R_{ct}^{\Delta \eta} + \Delta R_{ct}^{\Delta w}. \quad (1.25)
\]

Each decomposition works like a manual for constructing instruments; \(IV^{\Delta \eta}\) based on \(\Delta R_{ct}^{\Delta \eta}\)
and \(IV^{\Delta w}\) based on \(\Delta R_{ct}^{\Delta w}\):

\[
IV^{\Delta \eta} = \sum_i (\hat{\eta}_{cit} - \eta_{cit-1}) \sigma_{it-1}, \quad (1.26)
\]

\(^{18}\) 2008 World Trade Data, Trade Analyser, Computing in the Humanities and Social Sciences (CHASS),

\(^{19}\) U.S. Department of Transportation, Research and Innovative Technology Administration, Bureau of
where $\eta_{cit-1} = \frac{e_{c\it{it}-1}}{\sum_i e_{c\it{it}-1}}$ and $\tilde{\eta}_{cit} = \eta_{cit-1} + \Delta\tilde{\eta}_{cit}$, with $\Delta\tilde{\eta}_{cit}$ being the fitted values from the following regression:

$$\Delta\tilde{\eta}_{cit} = \tilde{\psi}_0 + \tilde{\psi}_1\eta_{cit-1} + \sum_x \tilde{\psi}_2 ln(dist_{cx}), \quad (1.28)$$

where $d_{cx}$ is the distance of city $c$ from major commercial border crossing $x$ on Mexico-U.S. border. The fitted values from equation (1.28) would generate changes in city-sector employment shares that only depend on the pre-trade structure of employment and distance of cities from the border.

To deal with the endogeneity of $\Delta ER_{ct}$, following similar steps are taken to create appropriate instruments for the change in employment rate:

$$\Delta \tilde{ER}_{cit} = \tilde{\varphi}_0 + \tilde{\varphi}_1 ER_{cit-1} + \sum_x \tilde{\varphi}_2 ln(dist_{cx}), \quad (1.29)$$

$$IV^{ER}_{c\it{it}} = \Delta \tilde{ER}_{cit}, \quad (1.30)$$

and

$$IV^{ER}_{c} = \sum_i IV^{ER}_{c\it{it}}. \quad (31)$$

It can be shown that under the same assumption required for the validity of instruments for the change in industrial composition, these instruments are also valid.

The major commercial Mexico-U.S. border crossings used as points of references for measuring distance are Laredo (Texas) with 37.5% share in border trade (dollar value) in 1999, El Paso (Texas) with 18.6% share, Otay Mesa-San Ysidro (California) with 9.3% share, Brownsville (Texas) with 6.2% share, Nogales (Arizona) with 6.1% share, Hidalgo (Texas) with
5.7% share, Calexico (California) with 4.7% share, and Eagle Paso (Texas) with 4.1% share. In 1999, 92.2% of total trade between Mexico and U.S. passed through these eight border crossings.20

Equality of OLS and IV estimates will be indicative of two important points: that OLS is consistently estimating the coefficients in equation (1.15) and that the stronger condition required for consistency of OLS is valid in the data (i.e., common city advantages are independent of relative advantages in pre- and post-trade era). Such a conclusion is valid to the extent that the assumptions required for validity of the instrumental approach are satisfied in the data.

Finally, to make sure that the OLS estimates are robust at the presence of alternative explanations for differences in wages across cities in the literature, such as those related to city education levels (Acemoglu and Angrist, 1999; Moretti, 2004), diversity of employment in a city (Glaeser, Kallal, Scheinkman, and Shleifer, 1992), and minimum wage regions (Fairris, Popli, and Zepeda, 2008), additional variables representing these alternative hypotheses will be added to equation (1.6).

1.4 Data

The data used here are extracted from the eleventh and twelfth waves of Mexican General Population and Housing Census for years 1990 and 2000, originally produced by the Mexican National Institute of Statistics, Geography, and Informatics21 and preserved and harmonized by Minnesota Population Center (2008). The sample is narrowed down to employed males and females aged 16 to 65, who are wage or salary workers in an identified industry, positive monthly income, who are living in a metropolitan area. The sample consists of 2,409,671 individual observations in 1990 and 2,409,254 observations in 2000, which are appropriately aggregated, using sampling weights, to form a panel of 15 broadly defined industries over 55 cities. Detailed industry groups are not consistently defined for the two years of the census and a match is not possible. Therefore, the recoded general definition of 15 sectors is being used instead, the list of which is provided in table (1.1). Since it was necessary in this study to appropriately define geographic limits of local labour markets, that are independent and are

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21 Instituto Nacional de Estadística, Geografía, e Informática (or INEGI in short)
comparable over time, the official definition of 55 metropolitan areas in Mexico\textsuperscript{22} is used (see figure 1.6 for the list and map of the metropolitan areas).

### 1.5 Estimation Results

This section describes the estimation results. First, the baseline results are reported and then likely issues that may be associated with it (selection bias and endogeneity) are dealt with. The robustness checks will from the last step. Overall, the results indicate a statistically significant, positive, and sizable causal relationship from the change in local industrial composition to city-industry wages that is robust to correction for selection bias and is not suffering from endogeneity.

#### 1.5.1 Baseline OLS Estimates

The baseline OLS results in table (1.2), which are reported for two different specification of equation (1.15) one with city employment rates as a control variable under OLS (1) and one with city-sector employment rates under OLS (2), indicate positive and statistically highly significant estimates of the coefficient of $\Delta R_c$. Controlling for changes in city employment rate or city-sector employment rates do not seem to have any effect on the size and significance of the coefficient of change in the measure of industrial composition. The change in employment rate, at city or city-industry level, is not statistically significant.

Figure (1.7) depicts the scatter diagram and fitted relationship of the controlled\textsuperscript{23} variation in the changes in city-sector wage and the measure of industrial composition. It appears that the results of the OLS may be affected by a data point at the top right corner of the scatter diagram, and another in the center of the diagram. However, as shown in figures (1.8) and (1.9), stepwise exclusion of these observations from the sample does not significantly changes the slope and significance of the fitted relationship. Also, given that the metropolitan area that includes Mexico City (Valle de Mexico) has a large concentration of most of the sectors in comparison to other cities, equation (1.15) was also estimated by dropping this metropolitan area from the sample. The results are not reported here as doing so does not change the previous results.


\textsuperscript{23} ‘Controlled’ here means that the variables graphed are in fact the residuals of their regression on changes in city-industry employment rates and industry fixed-effects.
If OLS consistently estimates the relationship between the local composition of employment and wages within cities, which relies on the set of assumptions reviewed in previous sections (and in detail in the appendix), the positive and statistically significant coefficient of $\Delta R_c$ is indicative of very important and interesting points. First, a positive and statistically-different-from-zero estimate indicates that local sectoral composition of employment is a relevant determinant of the long term changes in industrial wages in a city. It also supports the general equilibrium mechanism described above as possible conduit for changes in local industrial composition to affect wages within a city.

Second, the magnitude of the estimate points out that the general equilibrium wage impact of a shift in industrial composition is almost three times as big as the conventional accounting measures of such a shift. The conventional accounting approach measures the effect of a shift in industrial composition on the average wage by taking account of the shifts in employment shares (the weights) while keeping the wages fixed, i.e., by ignoring the general equilibrium effects of the shifts in employment shares on wages.

As explained under equation (1.10), measuring the average wage in a city by $\sum_i \eta_{ic} w_{ic}$, a shifts in industrial composition that increases the average wage by one unit will according to equation (1.10)\textsuperscript{24} will increase all wages in the city by $\gamma_2$ (which is the average of $\gamma_{c2}$ across cities) through general equilibrium spillover effects. The increases in wages increases the average wage by $\gamma_2$, which once again results in all wages in the city to increase by $\gamma_2^2$. This process continues till it dies off as $\gamma_2$ is smaller than one. By the time the new steady state is established, the total increase in the average wage will sum to $1 + \gamma_2 + \gamma_2^2 + \cdots = 1 + \frac{\gamma_2}{1-\gamma_2}$ that is the initial one unit increase in the average wage purely from the shift in industrial composition, which is the accounting measure of the effects of such a change on the average wage, plus its general equilibrium effect on wages. Thus, $\frac{\gamma_2}{1-\gamma_2}$ in fact measures the size of the total general equilibrium wage effect from the initial shift in the composition of employment relative to a pure shift-share accounting of its effects. The coefficient of the change in industrial composition in equation (1.15) exactly estimates $\frac{\gamma_2}{1-\gamma_2}$.

Hence, an estimate of $\beta = 2.6$ indicates the total general equilibrium wage effect of a shift in industrial composition is almost three times as big as its conventional accounting measures. In other words, a shift in local composition of employment that at fixed wages changes the average

\textsuperscript{24} See footnote 12.
wage by one percent will increase the average wage by about 2.6 percent, giving rise to long-run local industrial wage elasticity of 2.6 with respect to local industrial composition due to general equilibrium effects. The total effect of such a change in local composition of employment on the average wage is then 3.6 percent, 72% of which are due to the G.E. effects.

During the ten years from 1990 to 2000, in San Francisco del Rincón metropolitan area in central Mexico the measure of industrial composition increased by 0.053 units. This was mainly due to the large movements of labour into Manufacturing and out of Agriculture, which respectively pay the 7th highest and the lowest wages amongst the 15 sectors in Mexico. Given the estimate of the average G.E. wage impacts of shifts in industrial composition here, all wages in this city should have increased by about 14% during this period. During this period, average increase in industry wages in this city (excluding Real Estate and Business Services sector, which experienced an exceptional growth in wages to make it an outlier) was about 18%. In the absence of the G.E. wage impacts associated with movement across industries, average industry wages in this city and the wage in Agriculture would have increased by only 4%. This is while in Minatitlán in southern Mexico the measure of industrial composition decreased by -1.9% units due to large movements of workers out of the high-paying sectors such as Mining and Manufacturing into low-paying sectors such as Agriculture, Private Household Services, Whole Sale and Retail Trade, Hotels and Restaurants, and Education. Given the G.E. wage effects found here, it is no surprise that average change in industry wages in this city was about -8%, 63% of it due to the movement across industries.

Note that these figures amount to a spatial wage gap between the two cities of about 22% during the ten years from 1990 to 2000.

1.5.2 Correcting for Sample Selection Bias

The correction for sample selection is carried out following the approach in Dahl (2002). To calculate the probabilities of migration, the sample is divided into “movers” and “stayers”. Movers are individuals who at the time of census were living in a city that was not a part of the state they were born in. Stayers are individuals who were living in a city that is part of their state of birth. The movers are then divided into 80 different cells formed by five age categories, four education categories, two gender groups, and being indigenous. For the stayers, two additional categories were used to divide them into 320 cells, namely two groups for being married or not (spouse being present in the household) and two groups for having or not having at least one
child under the age of five present in the household. The higher number of divisions for the stayers is in accordance with their higher share in the sample. Using these divisions, the probability of migration, $P_{kbc}$, is defined as the fraction of individuals born in state $b$ that are in the same cell as person $k$ and have moved to city $c$. In a similar way, $P_{kbb}$, the probability of staying, is defined as the fraction of individuals born in state $b$ that are in the same cell as person $k$ and have stayed in the same state. Using these probabilities, the self-selection corrected national industry wage premia and city-industry wages were estimated according to equations (1.22) and (1.23), respectively. The probability terms in these equations turn out to be statistically significant, indicating that the sample suffers from self-selection.

The selection corrected OLS results, that appear under OLS (3) and (4) in table (1.2), show that the baseline OLS results are not biased as a result of self-selection. However, since in the process of correction for self-selection the probabilities of migration were statistically significant, indicating that the sample is affected by self-selection, the self-selection-corrected data is used for the rest of estimations as a cautionary measure.

### 1.5.3 Correcting for Endogeneity

Columns (1) and (2) under the IV section in table (1.2) report the results of using the instruments to estimate the parameters in equation (1.15). The results under IV (1) are associated with the specification that controls for the change in city-level employment rate, and under IV (2) with the specification that controls for the city-industry change in employment rate. The important 1st-stage statistics associated with the IV estimations are reported in the bottom part of table (1.2). All the IV results are also corrected for sample selection bias.

The IV results strongly confirm the OLS estimates, indicating that they do not suffer from endogeneity. The statistical similarity of estimates between the two approach points to the fact that the strong OLS identification assumption (contemporaneous independence of common city advantage terms from the structure of industrial employment within the city) is satisfied in the data.

It is important to note that as a result of using the distance-based instruments, what is identified here is the average wage effect of trade-induced changes in industrial composition and employment rate. In other words, the IV estimates are identified off of variations in the regressors that are correlated with their distance from major commercial Mexico-U.S. border crossings. To the extent that these distances indicate the variation across cities in the effects of
trade liberalization on within industry demands, what is identified here is the effect of the change in trade policy on local industrial wages, through induced changes in local employment rates and compositions of employment.

The 1st-stage results associated with the IV procedure show that the instruments perform satisfactorily. The p-value associated with the over-identification test indicates that the null hypothesis cannot be rejected. The null hypothesis in this test is that the instruments are valid and are correctly excluded from the equation being estimated. Rejection of the null would have casted doubt on the validity of the instruments and the identification assumption (independence of the improvements in common city advantage terms from pre-trade structures of employment across cities and their distance from the northern border). As far as the change in industrial composition is concerned, the distance-based instruments explain about 70% of the variations in this measure across cities.

In principle, the general equilibrium wage effects of a shift in industrial composition at constant wages should not be different from the wage effects of a shift in the wage premia at a given composition of employment. To empirically test this, the following specification is considered:

\[
\Delta w_{ci} = \alpha + d_i + \beta \Delta \eta \Delta R_c^{\Delta \eta} + \beta \Delta w \Delta R_c^{\Delta w} + \Delta ER_{ci} + \Delta \xi_{ci}, \quad (1.32)
\]

where \( \Delta R_c^{\Delta \eta} \) and \( \Delta R_c^{\Delta w} \) are respectively the share-based and premium-based changes in the measure of industrial composition, that were defined in equation (1.25). The OLS and IV estimation results of this specification are reported in table (1.3), again for two cases of controlling for city-level change in employment rate, under OLS (1) and IV (1), or controlling for city-industry level change in employment rate, under OLS (2) and IV (2). The data does not seem to support the theoretical conjecture above, as the IV estimates indicate the OLS results are not suffering from endogeneity and testing the equality of \( \beta \Delta \eta \) and \( \beta \Delta w \) based on the OLS estimates reject the null at 10% level of significance. This result is not consistent with the theoretical conjecture above and providing an explanation for it is left for future research. At this stage, this experiment gives reassurance that the share-based changes in the measure of industrial composition is still highly statistically significant.
1.5.4 Direct Estimation of the Reflection Specification

As a way to cross-check the results above and the effectiveness of the instruments, here the reflection specification (1.10) is directly estimated. Since under no circumstances the average wage in the right-hand-side can be treated as exogenous, directly estimating its coefficients under OLS and IV estimations would essentially be a test of whether the distance based instruments are effectively picking exogenous variations in the right-hand-side variables across cities.

Since the coefficients in (1.10) are implicit functions of city-level employment rate, taking a linear approximation of this specification at a point where there is no difference across cities in terms of productivity or job-creation advantages (ε’s and Ω’s are all zero) and differencing over time would give the following specification:

\[ \Delta w_{cit} = \psi_0 + \psi_1 i + \psi_2 \Delta W_{ct} + \psi_3 \Delta ER_{ct} + \zeta_{cit} \]  

(1.33)

where \( W_{ct} = \sum_i \eta_{cit} w_{cit} \) is the weighted sum of the logarithm of city-industry wages at the city level, or the city’s average wage, \( \zeta_{cit} \) is \( \gamma_1 \Delta \epsilon_{cit} \), and \( \psi_2 \) corresponds to \( \gamma_2 \) so that \( \psi_2 / (1 - \psi_2) \) should give an estimate of \( \beta \) in specification (1.15).

Table (1.4) reports the results of OLS and IV estimations of (1.33). Two specifications are considered: one that controls for change in city-level employment rate and another that controls for change in city-industry level employment rate. The OLS estimates are robust to correcting for sample selection bias, and the IV results indicate that at 10% level of significance the selection corrected OLS estimates suffer from endogeneity. The selection corrected OLS estimate of \( \psi_2 \) (which corresponds to \( \gamma_2 \)) is about 0.89, which gives an estimate of \( \beta \) of about 8.09. The IV results estimate \( \psi_2 \) to be about 0.75, which gives rise to an estimate of \( \beta \) of about 3, interestingly close to the estimates of \( \beta \) from equation (1.15). This experiment shows that the instrumental variable strategy is effective.

1.5.5 Robustness

The literature is suggestive of alternative explanations for differences in wages across cities such as those related to diversity of employment in a city (Glaeser, Kallal, Scheinkman, and Shleifer, 1992), education levels (Acemoglu and Angrist, 1999; Moretti, 2004), and minimum wages (Fairris, Ropli, and Zepeda, 2008). Additional variables representing these alternative
explanations are added to equation (1.15) to ensure of the robustness of the current findings. The results are shown in table (1.5). The main finding of this paper, the wage effect of shift in industrial compositions across cities, remains stable in size and highly significant at presence of such alternative mechanisms.

Glaeser et al. (1992) examine predictions of various theories of growth externalities (knowledge spillovers) within and between industries at city level in the U.S. during 1956 and 1987. They try to verify whether it is the geographic specialization or competition of geographically proximate industries that promote innovation spillovers and growth in those industries and cities. One measure of city growth they use is growth in wages. By testing empirically in which cities industry wages grow faster, as a function of geographic specialization and competition, they find that although specialization has no effects, diversity in a city helps wage growth of the industry. To control for such a mechanism, a measure of pre-trade industrial diversification in cities is introduced to equation (1.15), which is measured by one minus the Herfindahl index, or one minus the sum of squared sectoral employment shares in the city. The more diversified the industrial structure in a city, the lower should its Herfindahl index and the higher should this measure of industrial diversification be. If the finding of Glaeser et al. (1992) for the U.S. is valid in Mexico, a positive estimate of the coefficient of this variable is expected. The results are reported under columns OLS (1) and IV (1) in table (1.5), with the variable “diverse” representing such a mechanism.

The change in the measure of industrial composition is robust to introducing this alternative explanation for growth in wages at the city level. The measure of sectoral diversification appears to be significant both in OLS and after using instruments for $\Delta R_c$ and $\Delta ER_c$, but with a negative sign. In other words, cities that had a more diverse structure of employment – i.e., more equal employment shares across industries within a city – experienced lower growth rates in their industrial wages.

Moretti (2004) examines wages in U.S. cities in the 1980’s and finds that cities with greater increase in the proportion of workers with a BA or higher education have higher wage gains. Acemoglu and Angrist (1999) find weaker results for the impact of education using average years of education in a state. Here, it is already controlled for the level of education in estimating the sectoral wage premia and therefore, the measure of industrial compositions does not reflect cities with higher wages due to having higher levels education. However, both measures of education discussed in the two studies mentioned above are again controlled for here. One
measure is the change in the proportion of workers with a BA or higher education ($ΔBA +_c$) and the other is the changes in average years of schooling ($Δschlyr_T$). The results are shown under columns OLS (2) and IV (2) in table (1.5), where 1990 levels of these new variables are used as their instruments. The change in the measure of industrial composition is robust to introduction of these variables. Neither of the new variables is significant, which is closer to the results in Acemoglu and Angrist (1999).

Fairris et al. (2008) link the observed clustering in wage distributions to minimum wage multiples in Mexico and show that minimum wages, instead of setting a minimum bound on the wages of formal sectoral workers, serve as a norm for wage setting throughout the Mexican economy. They find evidence of clustering around multiples of the minimum wage, and some evidence suggesting that wage increases over time for certain occupations follow stipulated increases in the minimum wage. The data on minimum wages from Bank of Mexico’s Annual Report\textsuperscript{25} is used here to create appropriate measures of minimum wages at the level of metropolitan areas. This data provides this information for three broad geographic divisions of the municipalities in Mexico. Essentially, a number-of-worker weighted average of the minimum wages in the municipalities that form a metropolitan area is used as the measure of minimum wage at city level. The change in this measure is introduced as a control to equation (1.15), for which the initial minimum wage is used as the instrument. According to the results reported under columns OLS (3) and IV (3) in table (1.5), estimate of the coefficient of change in the measure of local industrial composition is robust to controlling for the change in city-level minimum wages. The change in minimum wages is not statistically significant.

Given that rural to urban migration is prevalent in the less developed countries, it is worthwhile to say a few words about how it might impact the estimate of the total general equilibrium wage effect of a shift in industrial composition of employment here. Given that the identification strategy relies on variations across cities, the main concern here is about the effect of rural-urban migration between cities on their sectoral compositions of employment. Consider a situation where labour force migrates from rural areas of a local labour market to the urban areas of another local labour market due to higher growth rates in wages in the destination. Such a pattern of migration should in the destination result in higher employment shares for sectors that are more of a fit for low-skill workers, which relatively have lower innate wage premia, and

\textsuperscript{25} Annual Report 2003, Bank De Mexico, Accessed on April 2004, p.139.
lower employment shares in similar industries at the origin. Therefore, this pattern of migration should decrease the measure of industrial composition in the fast-growth labour markets (destinations) and increase it in slow-growth ones (origins), generating an inverse relationship between the measure of industrial composition and wages across cities. This should dampen the estimate of the general equilibrium wage effects of shifts in industrial composition here since the idea is that cities undergoing a change in their mix of industries in favour of high-premium industries should experience higher average wages. Therefore, if anything, prevalence of rural-urban migration make the estimates here to be more conservative.

### 1.6 Conclusion

It was asked here whether the effect of trade liberalization on wages is limited only to its effect on demand for labour within the impacted industries or that the induced shifts in the composition of the overall demand also matter. Building on the theoretical model devised in Beaudry, Green, and Sand (2011) and using Mexican household census data for years 1990 and 2000, it was found that changes in industrial composition of the overall demand for labour across Mexican cities had substantial causal impact on local wages.

Industrial composition of employment is measured as local employment-share weighted sum of national industry wage premia. Essentially, it is estimated here that one percent increase in this measure, can raise local industrial wages by at least 2.6 percent, averaged across cities. Cities’ distances from major commercial Mexico-U.S. border crossing were used as indicators of distributive effects of trade liberalization on compositions of employment across Mexican cities. These distances were used to construct instrumental variables that help identify the trade-induced variation in compositions of employment across cities. The distance-based instruments explain 71% of the variation in the change in local compositions of employment across cities in Mexico during the 1990s.

Major changes in national trade or industrial policy are frequent in the less developed countries with already non-uniform distribution of economic development across regions, and can create geographic winners and losers depending on distribution of induced effects across space. The findings here are especially important in the context of these countries, where alleviation of poverty and geographically balanced distribution of purchasing power are among the priorities. In Mexico, while shifts in local industrial compositions toward higher paying industries helped raise earnings of workers in most cities during the 1990s, in some cities mostly
in South, due to reallocations away from high paying industries, the earnings declined or did not grow as fast. Given the large wage impacts found here, such patterns substantially contributed to worsening of the North-South wage gap in Mexico. The importance of a spatially balanced economic development accentuate the need for policy-analysis approaches that take into account such general equilibrium effects and address spatial heterogeneity of policy impacts across regions and localities.

An example is helpful in making this point more clear. During the ten years from 1990 to 2000, in San Francisco del Rincón metropolitan area in central Mexico the measure of industrial composition increased by 0.053 units. This was mainly due to the large movements of labour into Manufacturing and out of Agriculture, which respectively pay the 7th highest and the lowest wages amongst the 15 sectors in Mexico. Given the estimate of the average G.E. wage impacts of shifts in industrial composition here, all wages in this city should have increased by about 14% during this period. During this period, average increase in industry wages in this city (excluding Real Estate and Business Services sector, which experienced an exceptional growth in wages to make it an outlier) was about 18%. In the absence of the G.E. wage impacts associated with movement across industries, average industry wages in this city and the wage in Agriculture would have increased by only 4%. This is while in Minatitlán in southern Mexico the measure of industrial composition decreased by -1.9% units due to large movements of workers out of the high-paying sectors such as Mining and Manufacturing into low-paying sectors such as Agriculture, Private Household Services, Whole Sale and Retail Trade, Hotels and Restaurants, and Education. Given the G.E. wage effects found here, it is no surprise that average change in industry wages in this city was about -8%, 63% of it due to the movement across industries. These figures amount to a worsening of the spatial wage gap between the two cities averaging about 22%.
<table>
<thead>
<tr>
<th></th>
<th>List of Industries</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>Agriculture, Fishing, and Forestry</td>
</tr>
<tr>
<td>2</td>
<td>Mining</td>
</tr>
<tr>
<td>3</td>
<td>Manufacturing</td>
</tr>
<tr>
<td>4</td>
<td>Electricity, Gas, and Water</td>
</tr>
<tr>
<td>5</td>
<td>Construction</td>
</tr>
<tr>
<td>6</td>
<td>Wholesale and Retail Trade</td>
</tr>
<tr>
<td>7</td>
<td>Hotels and Restaurants</td>
</tr>
<tr>
<td>8</td>
<td>Transportation and Communication</td>
</tr>
<tr>
<td>9</td>
<td>Financial Services and Insurance</td>
</tr>
<tr>
<td>10</td>
<td>Public Administration and Defense</td>
</tr>
<tr>
<td>11</td>
<td>Real Estate and Business Services</td>
</tr>
<tr>
<td>12</td>
<td>Education</td>
</tr>
<tr>
<td>13</td>
<td>Health and Social Work</td>
</tr>
<tr>
<td>14</td>
<td>Other Community and Personal Services</td>
</tr>
<tr>
<td>15</td>
<td>Private Household Services</td>
</tr>
</tbody>
</table>
### Table (1.2) – OLS and IV Estimation Results of Equation (1.15)

<table>
<thead>
<tr>
<th>Dependent Variable: $\Delta w_{ci}$</th>
<th>OLS</th>
<th>Selection Corrected OLS</th>
<th>IV</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>(1)</td>
<td>(2)</td>
<td>(1)</td>
</tr>
<tr>
<td>$\Delta R_c$</td>
<td>2.61*** (0.82)</td>
<td>2.56*** (0.82)</td>
<td>2.66*** (0.83)</td>
</tr>
<tr>
<td>$\Delta E R_c$</td>
<td>-0.50 (0.75)</td>
<td>0.13 (0.51)</td>
<td>0.13 (0.52)</td>
</tr>
</tbody>
</table>

Industry Fixed Effects
- Yes

Corrected for Sample Selection
- Yes

Obs. 820

$R^2$ 0.20

1st-Stage Statistics

<table>
<thead>
<tr>
<th>Over-id Test P-value</th>
<th>0.15</th>
<th>0.12</th>
</tr>
</thead>
<tbody>
<tr>
<td>Partial $R^2$ of Excluded Instruments ($\Delta R_c$)$^*$</td>
<td>0.72</td>
<td>0.71</td>
</tr>
<tr>
<td>F-state ($\Delta R_c$)$^*$</td>
<td>52.1</td>
<td>42.1</td>
</tr>
<tr>
<td>P-value ($\Delta R_c$)$^*$</td>
<td>0.00</td>
<td>0.00</td>
</tr>
</tbody>
</table>

Partial $R^2$ of Excluded Instruments ($\Delta E R_c$)$^*$
- 0.29

F-state ($\Delta E R_c$)$^*$
- 12.0

P-value ($\Delta E R_c$)$^*$
- 0.00

Partial $R^2$ of Excluded Instruments ($\Delta E R_{ci}$)$^*$
- 0.42

F-state ($\Delta E R_{ci}$)$^*$
- 39.3

P-value ($\Delta E R_{ci}$)$^*$
- 0.00

($) : Robust, city-clustered standard deviation.  *, **, *** : Respectively, significance at 10%, 5%, and 1% levels of significance.  OLS (1): OLS estimation results of equation (1.15) controlling for the change in city employment rate rather.  OLS (2): OLS estimation results of equation (1.15) controlling for the change in city-sector employment rates.  IV (1): IV estimation results associated with the specification under Selection Corrected OLS (1) and using $IV_{\Delta \eta}$, $IV_{\Delta w}$ and $IV_{ER}$ as excluded instruments.  IV (2): IV estimation results of the specification under Selection Corrected OLS (2), using $IV_{\Delta \eta}$, $IV_{\Delta w}$, and $IV_{ER}$ as excluded instruments.  ♦: Squared-partial correlation between excluded instruments and the endogenous variable in the associated first stage regression.  ▼: The test is for the excluded instruments and robust to clustering and heteroskedasticity.
Table (1.3) – Decomposing $\Delta R_{ct} = \Delta R_{ct}^{\Delta \eta} + \Delta R_{ct}^{\Delta w}$

<table>
<thead>
<tr>
<th>Dependent Variable: $\Delta w_{ci}$</th>
<th>Selection Corrected OLS</th>
<th>IV</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\Delta R_{ct}^{\Delta \eta} = \sum_{i} \Delta \eta_{ct} \Delta \eta_{it-1}$</td>
<td>(1)</td>
<td>(2)</td>
</tr>
<tr>
<td>$\Delta R_{ct}^{\Delta w} = \sum_{i} \eta_{ct} \Delta \eta_{it}$</td>
<td></td>
<td></td>
</tr>
<tr>
<td>$\Delta ER_{ct}$</td>
<td>4.19***</td>
<td>3.96***</td>
</tr>
<tr>
<td></td>
<td>(0.97)</td>
<td>(0.98)</td>
</tr>
<tr>
<td>$\Delta ER_{ci}$</td>
<td>0.04</td>
<td>0.23</td>
</tr>
<tr>
<td></td>
<td>(1.47)</td>
<td>(1.51)</td>
</tr>
<tr>
<td></td>
<td>0.74</td>
<td>1.43</td>
</tr>
<tr>
<td></td>
<td>(0.73)</td>
<td>(0.54)</td>
</tr>
</tbody>
</table>

| Industry Fixed Effects ($d_i$) | Yes | Yes | Yes | Yes |
| Corrected for Sample Selection | Yes | Yes | Yes | Yes |
| Obs. | 820 | 820 | 820 | 820 |
| $R^2$ | 0.22 | 0.22 | 0.22 | 0.22 |
| P-value of the Test if: Coef. on $\Delta R_{ct}^{\Delta \eta}$ = Coef. on $\Delta R_{ct}^{\Delta w}$ | 0.03 | 0.05 | 0.12 | 0.11 |

1st-Stage Statistics

| Partial $R^2$ of Excluded Instruments ($\Delta R_{ct}^{\Delta \eta}$) | 0.61 | 0.59 |
| Partial $R^2$ of Excluded Instruments ($\Delta R_{ct}^{\Delta w}$) | 0.90 | 0.90 |
| Partial $R^2$ of Excluded Instruments ($\Delta ER_{ct}$) | 0.32 | 0.29 |
| Partial $R^2$ of Excluded Instruments ($\Delta ER_{ci}$) | 0.42 |

(•): Robust, city-clustered standard deviation. *, **, ***: Respectively, significance at 10%, 5%, and 1% levels of significance. OLS (1): OLS estimation results of equation (1.15) controlling for the change in city employment rate rather and with decomposed change in industrial composition. OLS (2): OLS estimation results of equation (1.15) controlling for the change in city-sector employment rates and with decomposed change in industrial composition. IV (1): IV estimation results associated with the specification under Selection Corrected OLS (1) and using $IV^{\Delta \eta}$, $IV^{\Delta w}$, and $IV^{ER}$ as excluded instruments. IV (2): IV estimation results of the specification under Selection Corrected OLS (2), using $IV^{\Delta \eta}$, $IV^{\Delta w}$, and $IV^{ER}$ as excluded instruments. ♣: Squared-partial correlation between excluded instruments and the associated left-hand-side first-stage variable. ♥: The test is robust to clustering and heteroskedasticity.
### Table (1.4) – OLS and IV Estimation Results of Reflection Equation (1.33)

<table>
<thead>
<tr>
<th>Dependent Variable: $\Delta w\text{ci}$</th>
<th>OLS</th>
<th>Selection Corrected OLS</th>
<th>IV</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>(1)</td>
<td>(2)</td>
<td>(1)</td>
</tr>
<tr>
<td>$\Delta W_c$</td>
<td>0.89*** (0.03)</td>
<td>0.89*** (0.03)</td>
<td>0.75*** (0.07)</td>
</tr>
<tr>
<td>$\Delta ER_c$</td>
<td>-0.03 (0.16)</td>
<td>-0.03 (0.15)</td>
<td>0.45 (0.33)</td>
</tr>
<tr>
<td>$\Delta ER_{ci}$</td>
<td>-0.26 (0.39)</td>
<td>-0.27 (0.38)</td>
<td>-0.26 (0.46)</td>
</tr>
</tbody>
</table>

| Industry Fixed Effects | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Corrected for Sample Selection | No | No | Yes | Yes | Yes | Yes |
| Obs.                    | 820 | 820 | 820 | 820 | 820 | 820 |
| $R^2$                   | 0.48 | 0.48 | 0.20 | 0.20 |

---

1st-Stage Statistics

<table>
<thead>
<tr>
<th></th>
<th>OLS (1)</th>
<th>OLS (2)</th>
<th>Selection Corrected OLS (1)</th>
<th>Selection Corrected OLS (2)</th>
<th>IV (1)</th>
<th>IV (2)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Over-id Test P-value</td>
<td>0.49</td>
<td>0.19</td>
<td>0.07</td>
<td>0.04</td>
<td>0.49</td>
<td>0.19</td>
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<tr>
<td>Endogeneity Test</td>
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<td>Partial $R^2$ of Excluded Instruments ($\Delta W_c$)*</td>
<td>0.16</td>
<td>0.15</td>
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<tr>
<td></td>
<td></td>
<td></td>
<td>F-state ($\Delta W_c$)*</td>
<td>6.02</td>
<td>7.40</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>P-value ($\Delta W_c$)*</td>
<td>0.00</td>
<td>0.00</td>
<td></td>
</tr>
<tr>
<td>Partial $R^2$ of Excluded Instruments ($\Delta ER_c$)*</td>
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<td></td>
<td>12.0</td>
<td>0.00</td>
<td></td>
<td></td>
</tr>
<tr>
<td>F-state ($\Delta ER_c$)*</td>
<td></td>
<td></td>
<td>0.00</td>
<td>0.00</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>Partial $R^2$ of Excluded Instruments ($\Delta ER_{ci}$)*</td>
<td>0.42</td>
<td></td>
<td></td>
</tr>
<tr>
<td>F-state ($\Delta ER_{ci}$)*</td>
<td></td>
<td></td>
<td>39.3</td>
<td>0.00</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>P-value ($\Delta ER_{ci}$)*</td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

(•) Robust, city-clustered standard deviation. *, **, ***: Respectively, significance at 10%, 5%, and 1% levels of significance. **OLS (1)**: OLS estimation results of equation (1.33) controlling for the change in city employment rate rather. **OLS (2)**: OLS estimation results of equation (1.33) controlling for the change in city-sector employment rates. **IV (1)**: IV estimation results associated with the specification under Selection Corrected OLS (1) and using $IV\Delta \eta$, $IV\Delta w$, and $IV^{ER}$ as excluded instruments. **IV (2)**: IV estimation results of the specification under Selection Corrected OLS (2), using $IV\Delta \eta$, $IV\Delta w$, and $IV^{ER}_{ci}$ as excluded instruments. ♣: Squared-partial correlation between excluded instruments and the endogenous variable in the associated first stage regression. ♠: The test is for the excluded instruments and robust to clustering and heteroskedasticity.


<table>
<thead>
<tr>
<th>Dependent Variable: ( \Delta w_{ct} )</th>
<th>City's Pre-trade Industrial Diversification</th>
<th>Change in City's Average Education (BA+)</th>
<th>Change in City's Average Education (Years of Schooling)</th>
<th>Change in Minimum Wage</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Selection Corrected</td>
<td>Selection Corrected OLS</td>
<td>Selection Corrected IV</td>
<td>Selection Corrected OLS</td>
</tr>
<tr>
<td></td>
<td>IV (1)</td>
<td>IV (2)</td>
<td>IV (3)</td>
<td>IV (4)</td>
</tr>
<tr>
<td>( \Delta R_c )</td>
<td>3.16***</td>
<td>2.27***</td>
<td>2.70***</td>
<td>3.19***</td>
</tr>
<tr>
<td></td>
<td>(0.63)</td>
<td>(0.82)</td>
<td>(0.80)</td>
<td>(0.82)</td>
</tr>
<tr>
<td>( \Delta E R_c )</td>
<td>-0.77</td>
<td>-1.41</td>
<td>-0.45</td>
<td>-0.19</td>
</tr>
<tr>
<td></td>
<td>(0.64)</td>
<td>(1.28)</td>
<td>(0.78)</td>
<td>(0.78)</td>
</tr>
<tr>
<td>( diverse_c )</td>
<td>-0.99***</td>
<td>-0.99***</td>
<td>-0.45</td>
<td>-0.19</td>
</tr>
<tr>
<td></td>
<td>(0.23)</td>
<td>(0.25)</td>
<td>(1.25)</td>
<td>(1.29)</td>
</tr>
<tr>
<td>( \Delta B A_{+c} )</td>
<td></td>
<td>-2.26**</td>
<td>-0.01</td>
<td>-1.51</td>
</tr>
<tr>
<td></td>
<td></td>
<td>(0.93)</td>
<td>(0.06)</td>
<td>(0.99)</td>
</tr>
<tr>
<td>( \Delta sc h l y r_c )</td>
<td></td>
<td></td>
<td>-0.35</td>
<td>-1.63</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>(0.18)</td>
<td>(1.11)</td>
</tr>
<tr>
<td>( \Delta m i n w a g e_c )</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Industry Fixed Effects ( d_i )</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>Corrected for Selection</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>Instrumented for Alternative Mechanism</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td></td>
<td>No</td>
<td>Yes</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Obs.</td>
<td>820</td>
<td>820</td>
<td>820</td>
<td>820</td>
</tr>
<tr>
<td>( R^2 )</td>
<td>0.27</td>
<td>0.22</td>
<td>0.20</td>
<td>0.22</td>
</tr>
<tr>
<td>Over-id Test P-value</td>
<td>0.66</td>
<td>0.04</td>
<td>0.29</td>
<td>0.12</td>
</tr>
</tbody>
</table>

(.): Robust, city-clustered standard deviation.  *, **, ***: Respectively, significance at 10%, 5%, and 1% levels of significance.
Figure (1.1) – Change in National Sectoral Employment Levels during 1990-2000 (Sorted according to the national sectoral wage premia increasing from left to right)
Figure (1.2) – Change in Regional Sectoral Employment Levels during 1990-2000 (Sorted according to the national sectoral wage premia increasing from left to right within regions)
Figure (1.3) – Change in Regional Sectoral Employment Levels during 1990-2000 (without Valle de Mexico & sorted according to the national sectoral wage premia increasing from left to right within regions)
Figure (1.4) – Change in National Sectoral Employment Shares during 1990-2000 (Sorted according to the national sectoral wage premia increasing from left to right)
Figure (1.5) – Change in Regional Sectoral Employment Shares during 1990-2000 (Sorted according to the national sectoral wage premia increasing from left to right within regions)
Figure (1.6) – Mexican Metropolitan Areas

Figure (1.7) – Controlled Correlation between the Change in City-Sector Wage and Change in Local Industrial Compositions

\[ \text{coef} = 2.61, \text{ (robust)} \ \text{se} = .83, \ t = 3.14 \]
Figure (1.8) – Controlled Correlation between the Change in City-Sector Wage and Change in Local Industrial Compositions after Removing the Likely Outlier

coef = 2.49, (robust) se = .82, t = 3.03
Figure (1.9) – Controlled Correlation between the Change in City-Sector Wage and Change in Local Industrial Compositions after Removing Both Likely Outliers

\[ \text{coef} = 2.49, \text{ (robust) se} = .82, t = 3.03 \]
Chapter 2


2.1 Introduction

Chapter 1 evaluated the wage effects of shifts in industrial composition of local employment across Mexican cities during the 1990s, the decade in which Mexico substantially opened liberalized its trade regime, and found that the local mix of industries played an important role in determining local industrial wages during the decade. This chapter evaluates the same mechanism in the context of Brazilian cities during the period in which Brazil underwent substantial trade liberalization, 1991-2000, to see if a similar causal relationship between long term changes in industrial composition and industrial wages can be found in the case of Brazil as well. Finding similar results here would complement the findings in Chapter 1 in providing evidence on wage effects of shifts in industrial composition of employment. It is important because the findings in Chapter 1 on Mexico may be seen as a special case due to having its single major trade partner, the U.S., just across from its northern border.

The question addressed is whether after controlling for changes in demand for labour the shifts in industrial composition of aggregate labour demand play an economically important role in determining wages. In exploring this question, this chapter also builds on the multi city, multi industry search and bargaining model of a labour market devised in Beaudry, Green, and Sand (2011) and uses the 1991 and 2000 waves of the Brazilian household census data\textsuperscript{26} to explore the long-term causal wage effects of shifts in composition of employment across Brazilian local economies, referred to as cities hereinafter. While conventionally it is assumed that shifts in industrial composition do not have important wage effects, Beaudry et al. (2011) show how in a search and bargaining framework a shift in sectoral composition of employment favouring high-wage industries can substantially increase wages across all sectors. As explained before in Chapter 1, such a compositional shift raises the value of the outside option for the bargaining unemployed workers within any skill-group, as it increases the likelihood of employment in

\textsuperscript{26} IPUMS-International, a project in the Minnesota Population Centre Data Projects at https://international.ipums.org/international, is to be highlighted as the provider of the data used in this study.
high-wage industries. Consequently, wages increase in all sectors. Whether such an effect is substantial is an empirical question in nature.

This mechanism opens a new way for looking into the wage effects of changes in trade or industrial policies as major trade or industrial policies affect within-industry demand for labour, and through differences in impacts across industries, also shift industrial composition of the aggregate labour demand. Like Mexico of the 1990s, Brazil is another interesting case study for exploring the general equilibrium wage effects associated with shifts in industrial composition of employment. Brazil underwent major trade liberalization and signed on to the South American free trade agreement (MERCOSUR) during the 1990s. Since 1987 Brazil gradually liberalized its trade regime and reduced its tariffs and non-tariff barriers\(^\text{27}\) (NTBs) to trade. Overall, average manufacturing tariffs in Brazil declined from about 60% in 1987 to 15% in 1998 and almost all NTBs were removed (Goldberg and Pavcnik, 2003). During 1991-2000, Brazil’s total merchandize export increased by 74.4% from US$31.6 billion to US$55.1 billion and its total merchandize import increased by 97.0% from US$30.0 billion to US$59.1 billion\(^\text{28}\).

Following the approach pursued in Chapter 1 and measuring industrial composition of local employment across cities as local sectoral employment-share weighted sum of national industrial wage premia\(^\text{29}\), geographical variation in this measure over time can be exploited to see whether local industrial wages vary systematically across cities with the changes in local compositions of employment, while controlling for the wage effects from changes in local employment rates. In principle, variations across local labour markets in change in local employment rates and composition of employment should allow for identification of their associated impacts on local industrial wages. However, due to the inherent simultaneity between these variables in a general equilibrium setting, exogenous variations in local employment rate and compositions of employment are needed to be able to consistently identify their associated wage effects.

Similar to the identification strategy used in Chapter 1, drawing on the insights from the New Economic Geography models\(^\text{30}\), an instrumental variable (IV) estimation strategy based on proximity of cities to major commercial ports of entry and exit in Brazil is devised here to identify exogenous trade-induced variations in the long term change in local compositions of

\(27\) Such as import licenses, special import programs, and administrative barriers to trade

\(28\) UNCTAD Handbook of Statistics, 2009. (Calculated at current prices and current exchange rates.)

\(29\) These are regression adjusted wages or the part of wages that cannot be explained by attributes of worker or cities and can be associated with industries.

\(30\) That distance as a trade barrier determines the size of trade between two economies.
employment across Brazilian cities, and consequently their causal impact on local industrial wages (see Combes et al., 2008; Da Mata et al., 2005; Fally et al., 2010; Hanson, 2005c; Head and Meyer, 2006; Hering and Poncet, 2008; Knaap, 2006; Mion and Naticchioni, 2005; Redding and Venables, 2004). The trade liberalization of the 1990s in Brazil is seen as the source of such exogenous variations. In particular, the pre-trade local structures of employment and distances of each city from a few major commercial ports of entry and exit in Brazil are used to predict the variations across cities in terms of the effects of trade liberalization of the 1990s on their local structures of employment. The idea is that the measures of distance indicate the transportation costs associated with each city and therefore indicate for each city the extent of its exposure to effects of trade liberalization.

The boom in trade relations in the aftermath of trade liberalization in Brazil substantially amplified the importance of access to foreign markets for its local economies. Other than Argentina, which shares a land border with Brazil in the South, the rest of Brazil’s major trade partners are widespread across the oceans. This has made the distance to the Argentina-Brazil border and major Brazilian commercial sea ports a key difference among cities in terms of their exposure to the trade boom and an important indicator of the geographic distribution of the impacts of change in trade policy across cities during this period. Sea ports alone handle 95% of Brazil’s trade by volume and 85% of its trade by value, leaving almost all of the remaining 15% to be handled by commercial border crossings in the south. This provides the rationale for using distances from major commercial sea ports in Brazil and border-crossings between Argentina and Brazil as indicators of how the effects of change in trade policy were distributed across different cities in Brazil.

Unlike Mexico that shares a border with its single major trade partner (the U.S.), Brazil has several major trade partners that are almost all located thousands of kilometers away from it; thus it may seem that the distance-based instrumental variables may not be of much help here. It turns out that the instruments help explain about 80% of the variation in the change in the measure of industrial composition during the 1990s across Brazilian cities. This is indicating that while the change in wages is unlikely to be directly determined by an exogenous, time invariant variable as such determined by nature (Glaeser, Rosenthal, & Strange, 2010), the extent of trade shock penetration is known to depend on factors such as being close to a good harbor (Disdier & Head, 2008).

See figure (2.1) for a map of the major Brazilian sea ports.
The findings here bring considerable evidence, indicating that aside from the wage effects of changes in city or city-industry level labour demands, shifts in local industrial compositions of employment had sizable impacts on sectoral wages across Brazilian cities. It is found here that a shift in the composition of employment that raise the measure of industrial composition by one percentage point, increases the sector-level wages by at least 2.2 percents averaged across cities. The IV results confirm the OLS findings. The estimate is shown to be robust to correcting for sample selection bias following the approach in Dahl (2002). Moreover, the findings are also robust to introduction of alternative explanations in the literature for differences in wage changes across cities, such as those related to diversity of employment in a city (Glaeser, Kallal, Scheinkman, and Shleifer, 1992) and levels of education (Acemoglu and Angrist, 1999; Duarte, Ferreira, and Salvato, 2004; Fally, Paillacar, and Terra, 2010; Moretti, 2004).

The finding of this paper is important in at least two respects. First, the large wage effect of shifts in industrial composition suggests that a proper evaluation of policy impacts should include such effects. Ex-ante evaluation of trade or industrial policies based on partial equilibrium assumptions and analysis (such as shift-share accounting) could miss effects that are crucially important in decision making about policy changes. Exp-post evaluation of policy impacts should also include general equilibrium interactions such as the one found here. Second, the finding of this paper highlights the role that changes in national trade or industrial policies play in creating (geographic) winners and losers depending on how their impacts are distributed sub-nationally to different localities. Given the sizable G.E. wage impacts found here, a spatially un-even pattern of shifts in composition of employment could significantly contribute to the worsening of spatial wage disparities and formation of wide spatial wage gaps. Both of these aspects are essentially important in the context of developing countries, given that they are relatively more prone to major policy changes as such and that spatially even provision of economic development or of their top priorities.

32 Socio-Economic data in Brazil is available for municipios, the main administrative level for local policy implementation and management, which due to strong economic links neighboring municipios cannot be considered as distinct labour market. They also vary dramatically in size and over time in boundaries. To properly define labour markets for the purpose of empirical analysis, this study adapts a grouping of municipios into 123 cities/metropolitan areas according to a comprehensive study by the Government of Brazil on characterization and trends of urban network in Brazil (IPEA, IBGE, & UNICAMP, 2002).

33 The change in logarithm of city-industry level wages has a mean of 0.30 across cities and a standard deviation of 0.169. The change in the measure of industrial composition has a mean of -0.03 across cities and a standard deviation of 0.014.
In the case of Brazil, the pattern of shifts in local industrial compositions in fact helped reduce the regional wage gap between the poor and rich areas in this country. As figures (2.1) to (2.10) illustrate, local industrial wages (averaged across cities and industries) in the historically poorest region of Brazil34 increased more than any other region35 during 1991-2000. However, as it appears from figures (2.6) to (2.7), it was not due to exceptional shifts in compositions of local employment in cities in this region in favour of high paying industries. Rather, it was mostly due to adverse shifts (toward low-paying industries) in local compositions of employment everywhere else in the country. As illustrated in figure (2.8), the measure of industrial composition, averaged across cities within regions, declined substantially lower in the North-East region than all other regions but the Midwest. The Midwest is relatively far from major commercial Argentina-Brazil border-crossings relative to the South and Southeast regions, and is far away from all the major commercial sea ports. As a result, trade liberalization affected the composition of cities in this region the least. This is while cities in the South and Southeast, being the historic manufacturing hubs in Brazil (see figure 2.6) and close to both Argentina and many major commercial sea ports (see figure 2.1), were quite adversely hit by the change in trade policy and experienced major declines in their measures of industrial compositions as a result.

The structure of the paper is as follows. Section 2.2 briefly describes the theoretical model that is used as a guide in the empirical section. Section 2.3 explains the empirical strategy and the necessary steps required before moving on to the estimation. Section 2.4 introduces the data and section 2.5 reports the results of the estimations. Section 2.6 concludes the paper.

### 2.2 Theory

The same model that was used in Chapter 1 is used here and therefore only important details of the model are reviewed again.36 The model shows how in a search and bargaining framework, changes in industrial composition employment affect sectoral wages. The intuition behind the model is as follows. It is assumed that workers are mobile across industries so that within any

---

34 A World Bank report calls the Northeast region the region with the “... most remaining income poverty ...” in Brazil (World Bank, 2001, p. 1). In a study on the evolution of the regional GDP’s in Brazil for the 1939-1998 period, Mossi et al. (2003) identify two spatial clusters in the country: a low-income one in the Northeast and a high-income one in the Southeast. Per capita income in São Paulo, the wealthiest Brazilian state, was 7.2 times that of Piauí, the poorest North Eastern state (Lall et al., 2004).

35 See figure (2.2) for the Regional Map of Brazil.

36 See the appendix for in-detail reproduction of the model in Beaudry et al. (2011).
skill-group unemployed workers search for employment opportunities across all sectors. It is also assumed that likelihood of finding a job in an industry is proportional to its share in employment. Given that industries pay differently to identical workers within a skill-group, a shift in industrial mix that favours higher-paying industries increases the likelihood of employment in high-premium industries, raises the value of outside options for unemployed workers, and improves their bargaining position in any skill-group and across all industries. Firms in all industries respond strategically and raise their wage offers. Therefore, the initial shift in the mix of industries favouring higher-paying industries result in spillover of higher wages in those industries to all industries and consequently increase wages across all industries. Whether this composition effect is economically important or not is an empirical question.

The economy is characterized by $C$ local economies (cities) in which firms produce goods and individuals seek employment over $I$ sectors. To produce and make profits, firms create new jobs and seek to fill the costly vacancies and weigh up the expected costs of keeping those vacancies against expected profits they make by employing workers and paying a wage that is city-sector specific. Each firm produces a sector specific product sold at a sector specific price. Similar to firms, individuals compare the expected benefits from being unemployed with accepting an employment offer at city-sector-specific wages. There is a random matching process through which workers are matched with firms. In steady-state equilibrium of this economy, the number of those matched is equal the death rate of matches and the value functions satisfy the standard Bellman relationship. All throughout the model it is assumed that workers are not mobile across cities, an assumption that if relaxed is not going to change the key result because before migration between cities equalizes wages everywhere no matter what the industrial compositions are, increases in the cost of amenities within cities (for example price of housing) will bring migration to a halt. Furthermore, to avoid corner solutions in which all production concentrates in one city or in several cities but in one industry, it is as assumed that cities have different advantages in different sectors. These city-sector advantages are defined by exogenous distributions that determine each city’s advantages and disadvantages in all sectors in terms of productivity and costs of creating vacancies within each sector. In equilibrium all the variables of the model, including city-industry wages and industries employment shares within a city, are functions of these exogenous city-sector advantage terms, which is a source of likely endogeneity later on when estimating the wage effects of shifts in composition of employment.
Without going into the details, solving the model for city-sector wages gives the following equilibrium relation:

\[ w_{ic} = \gamma_{c0} + \gamma_{c1}p_i + \gamma_{c2} \sum_j \eta_{jc} w_{jc} + \gamma_{c1} \epsilon_{ic}, \]  

(2.1)

where \( w_{ic} \) is the wage specific to industry \( i \) in city \( c \), \( p_i \) is the sector specific price of the sector specific product, \( \eta_{jc} \) represents the fraction of city \( c \)'s employment that is in industry \( j \), and \( \epsilon_{ic} \) is the exogenous advantage of city \( c \) in sector \( i \), in terms of the performance. The parameters in this equation are implicit functions of city-sector employment shares, city level employment ratios, the extent of mobility of labour across sectors, and exogenous city-sector performance advantage terms.

The derived equation for city-sector wages captures the notion that in a search and matching framework, sectoral wages act as strategic complements; that is, high wages in one sector are associated with high wages in other sectors.\(^{37}\) According to equation (2.1), an increase in wage in one sector in a city increases the average wage and consequently all wages in all sectors in the city. This makes impossible to estimate \( \gamma_{c2} \), the coefficient of city average wage. The strength of the strategic complementarity is captured by \( \gamma_{c2} \), which is implicitly a function of mobility of workers across sectors. If workers are immobile across sectors, \( \gamma_{c2} \) becomes zero, this effect disappears, and wages are determined solely by the value of marginal product.

According to equation (2.1), a pure shift in sectoral composition of employment that causes a one unit increase in the average city wage, \( \sum_j \eta_{jc} w_{jc} \), increases all sector-level wages in average by \( \gamma_{c2} \) in the city. But these increases in all city-sector wages cause the average wage to increase by another \( \gamma_{c2} \) units, generating a further round of adjustments. By the time the new steady state is established, the total effect of the pure change in sectoral composition on the average wage would therefore be \( \frac{1}{1-\gamma_{c2}} \), if \( \gamma_{c2} \) is smaller than one can be shown is the case here.

To deal with the reflection problem, and to directly show the impact of employment rate, manipulation\(^{38}\) of this equation results in the following equation:

\(^{37}\) For more details on the classic reflection or social interaction problem see Manski (1993) and Moffitt (2001).
\(^{38}\) To get equation (2.2), one should take a linear approximation of equation (2.1) at identical composition of employment across cities (\( \eta_{ic} = \eta_i = 1/I \)) and equal employment rates (\( ER_c = ER \)), which arises when there is no differences in city-sector advantages across cities, and assume that matching probabilities across cities and sectors

55
where \( d_i \) is a sector specific effect that can be captured in an empirical specification by including sector dummies, \( w_j - w_1 \) is the national level wage premium\(^{39} \) in sector \( j \) relative to sector 1, \( ER_c \) is the city level employment rate and the added coefficient, \( \gamma_{i5} \), reflects the effect of a change in the employment rate within a sector on wage determination in that sector. This coefficient may vary across sectors since the bargaining power of firms could depend on the tightness of labour market within each industry. Equation (2.2) shows how city-sector wages depend on the industrial composition of a city’s employments, captured by the term \( \sum_j \eta_{cj} (w_j - w_1) \). This term is denoted hereinafter by \( R_c \) and is referred to it as the measure of industrial composition\(^{40} \):

\[
R_c = \sum_j \eta_{cj} (w_j - w_1). \tag{2.3}
\]

Differencing the structural equation in (2.2) within a city-sector cell across two steady state equilibria, gives the following estimating equation:

\[
\Delta w_{ic} = \Delta d_i + \frac{\gamma_2}{(1 - \gamma_2)} \Delta R_c + \gamma_{i5} \Delta ER_c + \Delta \xi_{ic}, \tag{2.4}
\]

where \( \Delta d_i \) is a sector specific effect that can be captured in an empirical specification by including sector dummies, and \( \Delta \xi_{ic} = \gamma_1 \Delta \epsilon_{ic} + \gamma_1 \frac{\gamma_2}{(1 - \gamma_2)} \sum_j \frac{1}{I} \Delta \epsilon_{jc} \) is the error term with \( I \) being the total number of sectors.

are all the same, so that all the \( \gamma \) coefficients become nothing but the averages across cities at these similar matching probabilities. The details appear in the appendix.

\(^{39}\) Note that the theory is silent about attributes of workers, and specifically their skills. One should think of the wages and wage premia as calculated for one skill group so that an increase in the measure of industrial composition is not an increase of skill. In the empirics these will be obtained controlling for skills and other attributes of the workers.

\(^{40}\) Notice that a high value for the measure of industrial composition indicates that the city’s employment is concentrated in higher paying sectors.
The focus of the current study is on estimating the coefficient on the change in measure of industrial composition in equation (2.4); \( \frac{\gamma_2}{1-\gamma_2} \). Consistent estimates of this coefficient would shed light on the extent of city-level strategic complementarity between wages in different sectors by backing out \( \gamma_2 \). But the coefficient \( \frac{\gamma_2}{1-\gamma_2} \) is of interest in its own right as it provides an estimate of the general equilibrium effect of a one unit increase in the measure of industrial composition on within sector wages, as opposed to \( \gamma_2 \), which provides the partial unidirectional effect.\(^{41}\)

Examining wages in one sector in different cities, a positive value for \( \frac{\gamma_2}{1-\gamma_2} \) implies that for example agriculture wages will be higher in cities where employment is more heavily weighted toward high rent sectors, where high rent sectors are defined in terms of national level wage premia. This arises in the model because the unemployed workers in the Agriculture sector have better outside options in cities with higher share of their employment in high-rent industries.

Equation (2.4) will be used as the specification for the empirical analysis of the wage effects of shifts in industrial composition of employment. However, endogeneity of the variables in this equation puts the success of the OLS estimates in danger. In so far as the change in measure of industrial composition is concerned, the requirement for OLS to give consistent estimates of the coefficients in (2.4) is as follows:

\[
\text{plim}_{C, l \to \infty} \frac{1}{I} \sum_{i=1}^{I} \sum_{c=1}^{C} \Delta R_c \Delta \xi_{ic} = \text{plim}_{C, l \to \infty} \frac{1}{I} \sum_{c=1}^{C} \sum_{l=1}^{I} \Delta R_c \Delta \xi_{ic} = 0, \quad (2.5)
\]

recognizing that a similar condition is required for the change in employment rate. As shown in the appendix, since the error term is \( \Delta \xi_{ic} = \gamma_1 \Delta \epsilon_{ic} + \gamma_1 \frac{\gamma_2}{1-\gamma_2} \sum_{j=1}^{I} \Delta \epsilon_{jc} \), this condition effectively reduces to the properties of \( \epsilon_{ic} \), the city-industry productivity advantage terms. Both the measure of industrial composition and employment rates may be endogenous because they are functions of \( \eta_{ic} \)’s, which are correlated with the \( \epsilon \)’s. Intuitively, for equation (2.5) to be

\(^{41}\) \( \gamma_{2c} \) is a measure of the extent of strategic complementarity across industries within a city according to equation (2.1), which gave rise to the total \( \frac{1}{1-\gamma_{2c}} \) increase in average wages after a shift in industrial composition that directly increase the average in the equation by one unit. \( \gamma_2 \) is the average of \( \gamma_{2c} \) across cities with \( \frac{\gamma_2}{1-\gamma_2} \) being the general equilibrium wage effects of the initial shift in the industrial composition of employment.
satisfied the error terms, averaged across industries within cities, should be independent of both past and present structures of employment in all cities.\textsuperscript{42}

Since both of these assumptions together may not hold in the data, an instrumental approach is devised here that can consistently estimate the parameters in equation (2.4) under less stringent assumptions. Essentially, as shown in the appendix, under the assumption that the \( \epsilon \)'s are assumed to follow a random walk process with increments that are independent of the past and the proximity of cities to major commercial sea ports and Argentina border crossings in Brazil, an IV strategy is devised here.

A useful instrumental variable could be a suitable function of the initial period local employment shares and distances from border, that varies across cities and is highly correlated with the change in the measure of industrial composition across cities. The decomposition of changes in the measure of industrial compositions into two parts, one based on changes employment shares and the other based on changes in national wage premia, will be used as a guide in choosing the suitable functional form in generating the instruments\textsuperscript{43}. Section 2.3 presents a more detailed exposition of generating the instruments.

### 2.3 Empirical Strategy

The aim of this section is to explain the empirical strategy, potential issues, and necessary steps and approaches devised for a proper identification of the relationship between the measure of industrial composition and city-sector wages. Briefly, the empirical strategy here is to explore geographical variation in the change in industrial composition to see whether it is systematically related to the change in city-sector wages across cities, while controlling for the wage effects of change in local employment rate. Several preliminary steps are required to prepare the data for estimating the ultimate relationship of interest. Also, sample selection bias and endogeneity are potential issues that may jeopardize the success of the OLS estimation strategy. This section explains the preliminary steps and addresses several estimation issues.

The empirical estimating equation that closely matches equation (2.4) is specified as:

\[
\Delta w_{ci} = \alpha + d_i + \beta \Delta R_c + \Delta ER_{ci} + \Delta \xi_{ci} . \quad (2.6)
\]

\textsuperscript{42} These assumptions are discussed in the appendix in detail.

\textsuperscript{43} \( \Delta R_c = \Delta \sum_j \eta_{cj} \cdot (w_j - w_1) = \sum_j \Delta \eta_{cj} \cdot (w_j - w_1) + \sum_j \eta_{cj} \Delta (w_j - w_1) = \Delta R^\eta_c + \Delta R^\Delta w \)
where Δ indicates time difference over two distinct points (years 1991 and 2000) in time ten years apart from each other, for which the data is available. \( d_i \) indicates a full set of sector dummies excluding the base sector. The left hand side variable is the change wages specific to sector \( i \) in city \( c \), \( \Delta R_{ct} \) is the change in industrial composition of employment, and \( \Delta ER_{ci} \) is the change in city-industry employment rate, where city-industry employment rate is defined as the proportion of workers out of working age population employed in industry \( i \) in city \( c \). \( \Delta \xi_{cit} \) is the error term. \( \Delta ER_{ci} \) can also be replaced by \( \Delta ER_c \) to account for the wage effects of changes in the city-level labour demand.

The parameter of interest is \( \beta \) that captures the relationship between the measure of industrial composition and city-sector wages, while controlling for the impact of changes in the city or city-sector labour demand. In other words, in this specification the relationship captured by the estimates of \( \beta \) is in isolation from the wage effects induced by changes in the demand for labour. \( \beta \) captures the magnitude of the total G.E. effects of a shift in industrial composition on the average wage.

In estimation of equation (2.6) and conducting inferences, consistency of the estimates is crucial. Assuming consistent estimation, the goal would be to test the null hypothesis that \( \beta = 0 \). If the null cannot be rejected, the inter-sectoral wage interactions in the process of wage determination in local economies can be disregarded. On the other hand, a statistically significant and positive coefficient is indicative of a general equilibrium mechanism through which local sectoral composition of employment in average has a significant impact on city-industry wages across all cities. If this mechanism is estimated to be sizable, disregarding the general equilibrium impact on wages would be inappropriate.

In equation (2.6) the measure of industrial composition is computed as the weighted sum of national sectoral wage premia, using city-industry employment shares as the weights:

\[
R_{ct} = \sum_t \frac{e_{cit}}{\sum_i e_{cit}} \cdot \left( \frac{w_{it}}{w_{1t}} - 1 \right),
\]  

(2.7)
indicated by \( \frac{w_{it}}{w_{1t}} - 1 \). Note that the wage premium is expressed in percentages. A shift in the composition of employment favouring high-rent industries will increase this measure. At the same time, a change in the national industry wage premia in favour of the high-share industry also increases this measure. From the viewpoint of the theory, such changes in the wage premia at constant composition of employment should impact city-industry wages in the same way as a shift in the composition of employment favouring high-rent industries at constant wage premia does; both increase the value of an expected future employment.

Notice that as a result of measuring industrial composition using national wage premia, a city with relatively higher wages in all sectors is not necessarily going to have a higher measure of industrial composition, by construction. If the spillover mechanism from good jobs is at work, then, it is expected to see higher wages across all sectors in cities with higher measures of industrial composition.

If there are city-wide improvements that systematically move the measure of industrial composition and wages together, the OLS estimates are no more reliable. This is the intuitive interpretation of the identification assumption in equation (2.5) that is required for the consistency of the OLS estimates. To make sure of consistency of the OLS estimates, an IV approach will be devised to deal with the likely endogeneity of the regressors.

The industry specific wage premia are estimated from the individual data using the following specification estimated separately for each year:

\[
\ln(W_{kci}) = \varphi + \varphi_c d_c + X'_k \gamma + \sum \omega_i d_i + \epsilon_{kci}, \quad (2.8)
\]

where \( W_{kci} \) is the wage received by person \( k \) in city \( c \) working in sector \( i \), \( X_k \) denotes an array of the worker’s attributes, \( d_i \) and \( d_c \) indicate sector and city dummies, and \( ln(\cdot) \) is the natural logarithm function. In equation (2.8), estimates of \( \omega_i \)'s in each year by definition capture the national level sectoral wage premia relative to the base sector and can be used to replace the term \( \frac{w_{it}}{w_{1t}} - 1 \) in (2.7):

\[
R_{ct} = \sum_l \frac{e_{cit}}{\sum_l e_{cit}} \left( \frac{w_{it}}{w_{1t}} - 1 \right) \equiv \sum_l \frac{e_{cit}}{\sum_l e_{cit}} \omega_{ilt}. \quad (2.9)
\]
The next variable that requires attention is the left-hand-side variable in equation (2.6), $w_{cit}$. In the theoretical model, the worker is abstracted from all its attributes in the sense that the wages considered in the model are independent of the attributes of the workers and are *intrinsically* to the sector and city where they work.\(^{44}\) It is therefore necessary to adjust the data on individual wages for all the attributes for which information is available and properly aggregate the wages from individuals to the city-sector level. It is especially necessary in the case of Brazil since individual diversity is an important determinant of spatial wage differences in the country (see Fally et al., 2010). Duarte et al. (2004) show that differences in wages between the Northeast and Southeast regions in Brazil can be explained by differences in workers’ educational attainment. If such regional difference in the education levels of the workforce across regions can be explained by sorting (Combes and Duranton, 2006) or endogenous differences in returns to schooling (Redding and Schott, 2003), not controlling for the demographic differences across individuals may result in finding an artificial relationship between industrial composition of employment and wages due to the relationship between composition of workers and industrial composition of employment across different regions.

The coefficients of city-sector dummies in the following estimating equation can be considered as regression-adjusted wages for the attributes of workers averaged across individuals within each city-sector cell:

\[
\ln(W_{kci}) = \alpha + X_k'Y + \sum_c \sum_i w_{cit}d_{cti} + \omega_{kct}. \quad (2.10)
\]

Equation (2.10) can be estimated separately for each year using the sampling weights in the data so that each round of estimation generates the appropriately aggregated city-sector wages for that year.

In the same way as city-sector employment shares, the city level employment rates can also be computed directly from the data using the sampling weights. Having generated all the appropriate dependent and explanatory variables, equation (2.6) can be estimated to see whether changes in sectoral composition of employment in Brazilian cities systematically relay externalities on all local sector-level wages. Before moving on the estimation, it only remains to address the concerns about endogeneity and sample selection, as follows.

\(^{44}\) Another way to interpret this, is to say that the model is for a person with given skill level.
Finally, to make sure that the OLS estimates are robust at the presence of alternative explanations for differences in wages across cities in the literature, such as those related to city education levels (Acemoglu and Angrist, 1999; Moretti, 2004), diversity of employment in a city (Glaeser, Kallal, Scheinkman, and Shleifer, 1992), additional variables representing these alternative hypotheses will be added to equation (2.6).

### 2.3.1 Selection

In this section the concern about sample selection bias that the empirical strategy may suffer from is addressed. If workers are mobile across cities and choose where to live and work by comparing different cities in terms of their personal priorities, then individuals currently observed living in a city are not a random sample of the population. An individual’s wage is not observed in any city other than the one they choose to be a resident of at the time of census. This will compromise the conditions of zero mean error terms, required for the consistency of OLS estimates in estimation of industry specific wage premia and city-industry wages. In practice, in equations (2.8) and (2.10) this issue is in fact relevant in a conditional mean term; i.e., zero mean error conditioned on the wage figure being observed. Taking conditional expectations from equation (2.8) gives:

$$E[\ln(W_{kci})|X_k, d_i, and W_{kci} being observed] = \alpha + X'_k\gamma + \sum_i \alpha_id_i + E[\epsilon_{kci}|X_k, d_i, and W_{kci} being observed],$$  \hspace{1cm} (2.11)

where it is not clear if the conditional error mean term is actually zero in a sample suffering from self selection. If this is not the case, then the conditional residual mean term is correlated with other regressors and OLS is no more consistent.

Intuitively, if suddenly a group of individuals move from a city to another city in expectation of higher wages for reasons not observable but related to the structure of wages ($\Delta\xi_{ic}$), the change in the measure of industrial composition in equation (2.6) will also capture the impact of this sort of movements and the OLS estimation of this equation may give significantly-different-from-zero estimates of the relationship of interest without it really existing. Thus, it is very important to adjust the empirical strategy to correct for this possibility, which is carried out by implementing the approach in Dahl (2002), explained in section 1.3.1 of Chapter 1.
2.3.2 Endogeneity

Both the measure of industrial composition and employment rate are likely to be endogenous in a general equilibrium framework. As was indicated before and is reviewed in detail in the appendix, as far as the change in the measure of industrial composition is concerned the consistency of estimates of the parameters in equation (2.6) relies partly on the following condition:

\[
\lim_{C \to \infty} \frac{1}{C} \sum_{i=1}^{I} \sum_{c=1}^{C} \Delta R_c \Delta \xi_{ic} = \lim_{C \to \infty} \frac{1}{C} \sum_{c=1}^{C} \Delta R_c \sum_{i=1}^{I} \Delta \xi_{ic} = 0,
\]

where from the theoretical part \( \Delta \xi_{ic} = \gamma_1 \Delta \epsilon_{ic} + \gamma_2 \frac{1}{1-\gamma_2} \sum_{j=1}^{I} \Delta \epsilon_{jc} \). It was shown in section 1.3.2 in Chapter 1 that \( \sum \Delta \xi_{ic} \) can be interpreted as improvement in the cities’ average productivity advantage. Since employment shares used in the measure of industrial composition in each city are determined by the cities productivity advantage in industries (\( \epsilon_{ic} \)) as variations around the city’s average productivity advantage term (\( \tilde{\epsilon}_c \)), it can be shown that the condition for consistency of OLS estimates relies on the assumption that the common city-level advantages are independent of past and present relative advantages.

Under a weaker assumption that common city advantages are independent of proximity major commercial sea ports and Argentinean border crossings in Brazil, an instrumental variable approach is devised. It is hypothesized here that the trade-induced changes in the employment share of each industry varied across cities depending on their distance from major commercial sea port in Brazil and border crossings between Argentina and Brazil. Essentially, the trade induced changes in industry employment shares in each city will be predicted using the distances of that city from 15 major commercial sea ports (see figure 2.1) and from major commercial border crossings between Argentina and Brazil. These are then used to create instruments for the regressors in equation (2.6). Validity of this group of instruments relies as well on the same assumption mentioned above that the city common advantage terms follow a random walk process with increments independent of past and the distances.

To what extent is the assumption required for validity of distance-based instruments reasonable? Briefly, as long as changes in employment rate and industrial composition are

\[45\] A similar condition is required for the employment rate, \( \Delta ER_c \).
controlled for, distances from sea ports and the Argentina-Brazil border do not seem to belong to equation (2.6) as determinant of city-industry wages. In general, time invariant geographic attributes of a city such as it’s the distances used here are not expected to be part of the wage determination process in different cities. In other words two cities with different distances from border do not necessarily have different wage structures or wage growth trajectories. However, one may think possible that, because trade liberalization falls in the middle of the period being studied here, distance from border may have become relevant in the wage determination process in across cities. While being close to the capital city or other major cities was an advantage in the pre-trade liberalization era, in its aftermath being close to Argentina or the sea ports might have become an advantage (or a disadvantage). Hence, is the identification assumption mentioned above. Nevertheless, as far as the wage determination process is concerned, what is conceived as advantage in cities closer to or farther from the sea ports and Argentina is because of the distributive labour demand and supply effects of the change in trade policy (trade liberalization and MERCOSUR) across different cities, which should affect the wage determination process through changes in demand for labour in cities and sectors or the supply of labour. Labour demand effects of trade on wages are relayed through the trade-induced changes employment rate and industrial composition, both of which are controlled for in equation (2.6), or through increase in migrants in search of work that were corrected for through correction of sample selection bias. In other words, if there is a relationship between distance from border and changes in city-sectoral wages, it should be through mechanisms that are already controlled for in IV estimation of equation (2.6).

To what extent are distances from sea ports and Argentina border relevant? Since 1987 Brazil gradually liberalized its trade regime and reduced its tariffs and non-tariff barriers\(^\text{46}\) (NTBs) to trade. Overall, average manufacturing tariffs in Brazil declined from about 60% in 1987 to 15% in 1998 and almost all NTBs were removed (Goldberg and Pavcnik, 2003). During 1991-2000, Brazil’s total merchandize export increased by 74.4% from US$31.6 billion to US$55.1 billion and its total merchandize import increased by 97.0% from US$30.0 billion to US$59.1 billion.\(^\text{47}\) Also, the full enactment of the regional free trade agreement between Argentina, Brazil, Paraguay, and Uruguay (MERCOSUR)\(^\text{48}\) in 1995 falls in the middle of the horizon of this study.

\(^{46}\) Such as import licenses, special import programs, and administrative barriers to trade

\(^{47}\) UNCTAD Handbook of Statistics, 2009. (Calculated at current prices and current exchange rates.)

\(^{48}\) MERCOSUR or the Common Market of the South was founded in 1991 and was fully enacted in 1995. For more information see [www.mercosur.int](http://www.mercosur.int).
This agreement made Argentina to become a major trade partner of Brazil. Within manufacturing, Brazil’s imports from the US increased by 153% percent and its exports to the US increased by 102%. Respectively, the same statistics for Argentina is 313% and 305%, for Germany is 127% and 8.46% and, for Japan is 131% and -5.84%, for Italy is 170% and 30.1%, for France is 205% and 36.3%, for UK is 167% and 34.1%, and for China is 1,783% and 370%.\textsuperscript{49}

Such a boom in trade relations in the aftermath of trade liberalization in Brazil has substantially amplified the importance of access to foreign markets for its local economies. Other than Argentina, which shares a land border with Brazil in the South, the rest of Brazil’s major trade partners are widespread across the oceans. This has made distance to the Argentina-Brazil border and major Brazilian commercial sea ports a key difference among cities in terms of their exposure to the trade boom and an important indicator of the geographic distribution of the impacts of change in trade policy across cities during this period. Sea ports\textsuperscript{50} alone handle 95% of Brazil’s trade by volume and 85% of its trade by value, leaving almost all the other 15% of it to be handled by commercial border crossings in the south with Argentina. This provides the rational for using distances from major commercial sea ports in Brazil and border-crossings between Argentina and Brazil as indicators of how the effects of change in trade policy were distributed across different cities in Brazil.

The instruments are constructed based on the decomposition of $\Delta R_{ct}$ into a part that captures the change in the measure of industrial composition resulting from changes in employment shares ($\Delta R_{ct}^{\Delta \eta}$ below) and another that captures the changes resulting from variations in national level wage premia of sectors ($\Delta R_{ct}^{\Delta w}$ below):

$$\Delta R_{ct} = \sum_i (\eta_{cit} - \eta_{cit-1})\sigma_{it-1} + \sum_i \eta_{cit} (\sigma_{it} - \sigma_{it-1}) = \Delta R_{ct}^{\Delta \eta} + \Delta R_{ct}^{\Delta w}. \quad (2.15)$$

Each decomposition works like a manual for constructing instruments; $IV^{\Delta \eta}$ based on $\Delta R_{ct}^{\Delta \eta}$ and $IV^{\Delta w}$ based on $\Delta R_{ct}^{\Delta w}$.

\textsuperscript{49} NBER-United Nations Trade Data, \url{http://cid.econ.ucdavis.edu/}.

\textsuperscript{50} See figure (2.1) for a map of the major Brazilian sea ports.
\[ IV^{\Delta \eta} = \sum_{i} (\hat{\eta}_{citi} - \eta_{ci\_t-1}) \omega_{it-1}, \quad (2.16) \]

\[ IV^{\Delta \omega} = \sum_{i} \hat{\eta}_{citi} (\omega_{it} - \omega_{it-1}), \quad (2.17) \]

where \( \eta_{ci\_t-1} = \frac{e_{ci\_t-1}}{\sum_i e_{ci\_t-1}} \) and \( \hat{\eta}_{citi} = \eta_{ci\_t-1} + \Delta \hat{\eta}_{citi} \), with \( \Delta \hat{\eta}_{citi} \) being the fitted values from the following regression:

\[ \Delta \hat{\eta}_{citi} = \hat{\psi}_0 + \hat{\psi}_1 \eta_{ci\_t-1} + \sum_x \hat{\psi}_2 \ln (dist_{cx}), \quad (2.18) \]

where \( d_{cx} \) is the distance of city \( c \) from major commercial sea port or Argentina border crossing \( x \) in Brazil. The fitted values from equation (2.18) would generate changes in city-sector employment shares that only depend on the pre-trade structure of employment and distance of cities from the border.

To deal with the endogeneity of \( \Delta ER_{ct} \), following similar steps are taken to create appropriate instruments for the change in employment rate:

\[ \Delta \bar{E}R_{citi} = \bar{\phi}_0 + \bar{\phi}_1 ER_{ct-1} + \sum_x \bar{\phi}_2 dist_{cx}, \quad (2.19) \]

\[ IV^{ER}_{ci} = \Delta \bar{E}R_{citi}, \quad (2.20) \]

and

\[ IV^{ER}_c = \sum_l IV^{ER}_{cl}. \quad (2.21) \]
2.4 Data

The data used here are extracted from the tenth and eleventh Brazilian General Censuses for years 1991 and 2000, originally produced by the Brazilian Institute of Geography and Statistics (IBGE) and preserved and harmonized by Minnesota Population Center (2008). The sample is narrowed down to employed males and females aged 16 to 65, numbering to 1,961,783 and 2,454,603 individual observations, respectively for years 1991 and 2000.

Since the identification relies on variations across distinct local labour markets, it is necessary to define geographic limits that are consistent and comparable over time, are large enough so that residents do not commute beyond the boundaries to work, and are numerous. Ideal is to have a large number of time-consistent metropolitan areas in the sample. While Brazil is highly urbanized (80% of population and 90% of GDP), no official statistical or administrative entity is defined and included in the Brazilian census data reflects the concept of an economically independent city or urban agglomeration that is appropriate for economic analysis. The Brazilian census data is available for municipios, the main administrative level for local policy implementation and management, which are too small and too close to each other to be considered as independent economies and vary dramatically in size both between themselves and over time.

To properly define labour markets for the purpose of empirical analysis, this study adapts a grouping of municipios into 123 cities/metropolitan areas according to a comprehensive study done by the Government of Brazil on characterization and trends of urban network in Brazil (IPEA, IBGE, & UNICAMP, 2002). Figure (2.11) maps these distinct labour markets.

The detailed census industry definitions are also not comparable over time and hence impossible to match. This has forced the use of only fifteen, broadly defined industries here, namely Agriculture, fishing, and forestry, Mining, Manufacturing, Electricity, gas and water, Construction, Wholesale and retail trade, Hotels and restaurants, Transportation and communications, Financial services and insurance, Public administration and defense, Real estate and business services, Education, Health and social work, Other services, and Private household services. A higher number of industries would have been preferred but due to impossibility of matching the definition of industries across years in the census only the use of

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51 Instituto Brasileiro de Geografia e Estatística (or IBGE in short).

52 Population in Sao Paulo municipio about ten million while many other municipios with only a few thousand residents.
these 15 major categories was feasible. However, as argued in the appendix to this chapter, this has no bearing on the consistency of OLS estimates or validity of instruments.

Using sampling weights, the data is properly aggregated from individual level into 123 cities over 15 broadly defined industries for the two years. This gives a panel with 1,845 observations each year, for years 1991 and 2000. The square root of the number of sample observations used for calculating each observation in the panel is used as an analytical weight in the estimating equations.

2.5 Estimation Results

This section describes the estimation results. First, the baseline results are reported and then likely issues that may be associated with it (selection bias and endogeneity) are dealt with. The robustness checks will from the last step. Overall, the results indicate a statistically significant, positive, and sizable causal relationship from the change in local industrial composition to city-industry wages that is robust to correction for selection bias and is not suffering from endogeneity.

2.5.1 Baseline Estimation Results

The baseline OLS results in table (2.1), which are reported for two different specification of equation (2.6) one with city employment rates as a control variable under OLS (1) and one with city-sector employment rates under OLS (2), indicate positive and statistically highly significant estimates of the coefficient of \( \Delta R_c \). Controlling for changes in city employment rate or city-sector employment rates do not seem to have any effect on the size and significance of the coefficient of change in the measure of industrial composition. While the change in employment rate at city level is not significant, at city-industry level it is highly significant and positive. Figure (2.12) depicts the scatter diagram and fitted relationship of the controlled\(^53\) variation in the changes in city-sector wage and the measure of industrial composition.

If OLS consistently estimates the relationship between the local composition of employment and wages within cities, which relies on a set of assumptions reviewed in previous sections (and in detail in the appendix), the positive and statistically significant coefficient of \( \Delta R_c \) is indicative of very important and interesting points. First, a positive and statistically-different-from-zero

\(^53\) ‘Controlled’ here means that the variables graphed are in fact the residuals of their regression on changes in city-industry employment rates and industry fixed-effects.
estimate indicates that local sectoral composition of employment is a relevant determinant of the long term changes in industrial wages in a city. It also supports the general equilibrium mechanism described above as possible conduit for changes in local industrial composition to affect wages within a city.

Second, the magnitude of the estimate points out that the general equilibrium wage impact of a shift in industrial composition is almost two times as big as the conventional accounting measures of such a shift. The conventional accounting approach measures the effect of a shift in industrial composition on the average wage by taking account of the shifts in employment shares (the weights) while keeping the wages fixed, i.e., by ignoring the general equilibrium effects of the shifts in employment shares on wages.

As explained under equation (2.1), measuring the average wage in a city by $\sum \eta_{ic} w_{ic}$, a shift in industrial composition that increases the average wage by one unit will according to equation (2.1)$^{54}$ will increase all wages in the city by $\gamma_2$ (which is the average of $\gamma_{c2}$ across cities) through spillover over effects resulting from improving the bargaining position of unemployed workers. The increases in wages increases the average wage by $\gamma_2$, which once again results in all wages in the city to increase by $\gamma_2^2$. This process continues till it dies off as $\gamma_2$ is smaller than one. By the time the new steady state is established, the total increase in the average wage will sum to $1 + \gamma_2 + \gamma_2^2 + \cdots = 1 + \frac{\gamma_2}{1-\gamma_2}$ – that is the initial one unit increase in the average wage purely from the shift in industrial composition, which is the accounting measure of the effects of such a change on the average wage, plus its general equilibrium effect on wages. Thus, $\gamma_2$ in fact measures the size of the total general equilibrium wage effect from the initial shift in the composition of employment relative to a pure shift-share accounting of its effects. The coefficient of the change in industrial composition in equation (2.6) exactly estimates $\frac{\gamma_2}{1-\gamma_2}$.

Hence, an estimate of $\beta = 2.2$ indicates the total general equilibrium wage effect of a shift in industrial composition is at least 2.2 times as big as its conventional accounting measures. In other words, a shift in local composition of employment that at fixed wages changes the average wage by one percent will increase the average wage by about 2.2 percent, giving rise to long-run local industrial wage elasticity of 2.2 with respect to local industrial composition due to general equilibrium effects. The total effect of such a change in local composition of employment on the average wage is then 3.2 percent, 69% of which are due to the G.E. effects. The magnitude of

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$^{54}$ See footnote 47.
the estimate here should be interpreted as a conservative estimate as it will be shown that it could get as big as 4.

An example would be helpful here. The average change in the measure of industrial composition during 1991-2000 across cities in Brazil was about -3% with a standard deviation of 1.4% percentage points. The greater area of Corumbá in the state of Mato Grosso do Sul in the Midwest has a distance of about 1,100 Km from the closest Brazil-Argentina commercial border crossing and about 1,608 Km from the closest major commercial sea port (port of São Francisco do Sul). In this city, the measure of industrial composition changed by -1.36% during 1991-2000, almost one standard deviation above the average. Average change in industrial wages in this city was about 25.6% during the same period. The greater area of Araraquara in the state of São Paulo in the Southeast of Brazil has a distance of about 908 Km from the closest Brazil-Argentina commercial border crossing – which is almost the same as the city of Corumbá – but has a distance of about 350 Km from the closest major commercial sea port (port of Santos, the largest sea port in South America located in the state of São Paulo) – much closer to a major commercial sea port than the city of Corumbá. In this city, the measure of industrial composition changed by -4.55% during 1991-2000, almost one standard deviation below the average. It is no surprise that this city experiences an average change in industrial wages of only about 16.5% – that is about 55% lower than in Corumbá. Such a difference in average increase in local industrial wages amounted to a very wide spatial wage gap (55%) between the two cities during the ten year from 1990 to 2000.

### 2.5.2 Correcting for Sample Selection Bias

The correction for sample selection is carried out following the approach in Dahl (2002). To calculate the probabilities of migration, the sample is divided into “movers” and “stayers”. Movers are individuals who at the time of census were living in a city that was not a part of the state they were born in. Stayers are individuals who were living in a city that is part of their state of birth. The movers are then divided into 18 different cells formed by three age categories, three education categories, and two gender categories. For the stayers, an additional category was used to divide them into 36 cells, namely two groups for marital status (single or otherwise). In this way, a total of 36 cells are generated for the stayers. The higher number of divisions for the stayers is in accordance with their higher share in the sample. Using these divisions, the probability of migration, \( P_{kbc} \), is defined as the fraction of individuals born in state \( b \) that are in
the same cell as person $k$ and have moved to city $c$. In a similar way, $P_{kbb}$, the probability of staying, is defined as the fraction of individuals born in state $b$ that are in the same cell as person $k$ and have stayed in the same state. Using these probabilities, the self-selection corrected national industry wage premia and city-industry wages were estimated according to equations (2.13) and (2.14), respectively. The probability terms in these equations turn out to be statistically significant, indicating that the sample suffers from self-selection.

The selection corrected OLS results, that appear under OLS (3) and (4) in table (2.1), show that the baseline OLS results are not biased as a result of self-selection. However, since in the process of correction for self-selection the probabilities of migration were statistically significant, indicating that the sample is affected by self-selection, the self-selection-corrected data is used for the rest of estimations as a cautionary measure.

2.5.3 Correcting for Endogeneity

Columns (1) and (2) under the IV section in table (2.1) report the results of using the instruments to estimate the parameters in equation (2.6). The results under IV (1) are associated with the specification that controls for the change in city-level employment rate, and under IV (2) with the specification that controls for the city-industry change in employment rate. The important 1st-stage statistics associated with the IV estimations are reported in the bottom part of table (2.1). All the IV results are also corrected for sample selection bias.

The IV results strongly confirm the OLS estimates, indicating that they do not suffer from endogeneity. The statistical similarity of the estimates between the two approaches points to the fact that the strong OLS identification assumption (contemporaneous independence of common city advantage terms from the structure of industrial employment within the city) is satisfied in the data.

It is important to note that as a result of using the distance-based instruments, what is identified here is the wage average effect of trade-induced changes in industrial composition and

---

55 The test for equality of the OLS and IV estimates is formally carried out in this section by testing for exogeneity of the variable(s) of interest, separately or jointly, through comparing the distance of the OLS and IV estimates from each other via the endogtest(.) option of the ivreg2 command in STATA. The null hypothesis is that the specified endogenous regressor can actually be treated as exogenous, i.e., the IV estimates it is not significantly different from the OLS estimate for the variable(s) being tested. The P-value for the case of the estimates reported under column IV(1) in table (2.1) is 0.12 for $\Delta R_c$ and 0.23 for $\Delta ER_{ci}$, and 0.30 jointly, indicating the null cannot be rejected for both variable. Under IV(2) in the same table, the P-value for the estimates reported are 0.17 for $\Delta R_c$ and 0.23 $\Delta ER_{ci}$, and 0.23 jointly, indicating that both variables can be treated as exogenous.
employment rate. In other words, the IV estimates are identified off of variations in the regressors that are correlated with their distance from major commercial sea ports in Brazil\(^{56}\) and border crossings between Argentina and Brazil. To the extent that these distances indicate the distributive effects of trade liberalization across cities, what are identified here are the effects of the change in trade policy on local industrial wages, through induced changes in local employment rates and compositions of employment.

The 1\(^{st}\)-stage results associated with the IV procedure show that the instruments perform satisfactorily. The p-value associated with the over-identification test indicates that the null hypothesis cannot be rejected. The null hypothesis in this test is that the instruments are valid and are correctly excluded from the equation being estimated. Rejection of the null would have casted doubt on the validity of the instruments and the identification assumption (independence of common city advantage terms from pre-trade structures of employment across cities and their distance from the northern border). As far as the change in industrial composition is concerned, the distance-based instruments explain about 80% of the variations in this measure across cities.

Theoretically, the wage effects of changes in industrial composition should not be different if the source of the change is a shift in the composition at constant wages, or a shift in the wage premia at a given composition of employment. To empirically test this, the following specification is considered:

\[
\Delta w_{ci} = \alpha + d_i + \beta \Delta \eta \Delta R^\Delta \eta_c + \beta \Delta \omega \Delta R^\Delta \omega_c + \Delta ER_{ci} + \Delta \xi_{ci}, \quad (2.22)
\]

where \(\Delta R^\Delta \eta_c\) and \(\Delta R^\Delta \omega_c\) are respectively the share-based and premium-based changes in the measure of industrial composition, that were defined in equation (2.15). The OLS and IV estimation results of this specification are reported in table (2.2), again for two cases of controlling for city-level change in employment rate, under OLS (1) and IV (1), or when controlling for city-industry level change in employment rate, under OLS (2) and IV (2). The equality of the two estimates (of \(\beta \Delta \eta\) and \(\beta \Delta \omega\)) cannot be rejected in the data confirming the prediction of the theoretical model, but the second effect (the premium-based change in the

\(^{56}\) These major ports are: Port Santos (Santos - SP), Port Vitória (Vitória - ES), Port Paranaguá (Paranaguá - PR), Port Itaguai (Itagüí - RJ), Port Rio Grande (Rio Grande - RS), Port Rio de Janeiro (Rio de Janeiro - RJ), Port Itajaí (Itajaí - SC), Port Ilha (São Luís - MA), Port São Sebastião (São Sebastião - SP), Port São Francisco do Sul (São Francisco do Sul - SC), Port Aratu (Candeias - BA), Port Manaus (Manaus - AM), Port Suape (Ipojuca - PE), Port Pecém (São Gonçalo do Amarante - CE), Port Ilhéus (Ilhéus - BA). See figure 2.1 for a map of the ports.
measure of industrial composition) is not statistically significant. This experiment gives this reassurance that the share-based change in the measure of industrial composition is highly statistically significant.

2.5.4 Direct Estimation of the Reflection Specification

As a way to cross-check the results above and the effectiveness of the instruments, here the reflection specification (2.1) is directly estimated. Since under no circumstances the average wage in the right-hand-side can be treated as exogenous, directly estimating its coefficients under OLS and IV estimations would essentially be a test of whether the distance based instruments are effectively picking exogenous variations in the right-hand-side variables across cities.

Since the coefficients in (2.1) are implicit functions of city-level employment rate, taking a linear approximation of this specification at a point where there is no difference across cities in terms of productivity or job-creation advantages (ε’s and Ω’s are all zero) and differencing over time would give the following specification:

\[
\Delta w_{ct} = \psi_0 + \psi_1 t + \psi_2 \Delta W_{ct} + \psi_3 \Delta ER_{ct} + \zeta_{cit} \tag{2.23}
\]

where \( W_{ct} = \sum \eta_{cit} w_{cit} \) is the weighted sum of the logarithm of city-industry wages at the city level, or the city’s average wage, \( \zeta_{cit} \) is \( \gamma_1 \Delta \epsilon_{cit} \), and \( \psi_2 \) corresponds to \( \gamma_2 \) so that \( \psi_2 / 1 - \psi_2 \) should give an estimate of \( \beta \) in specification (2.6).

Table (2.4) reports the results of OLS and IV estimations of (2.23). Two specifications are considered: one that controls for change in city-level employment rate and another that controls for change in city-industry level employment rate. The OLS estimates are robust to correcting for sample selection bias, and the IV results indicate that at 10% level of significance the selection corrected OLS estimates suffer from endogeneity. The selection corrected OLS estimate of \( \psi_2 \) (which corresponds to \( \gamma_2 \)) is about 0.89, which gives an estimate of \( \beta \) of about 8.09. The IV results estimate \( \psi_2 \) to be about 0.67, which gives rise to an estimate of \( \beta \) of about 2, interestingly close to the estimates of \( \beta \) from equation (2.6). This experiment shows that the instrumental variable strategy is effective.


2.5.5 Robustness

The literature is suggestive of alternative explanations for differences in wages across cities such as those related to diversity of employment in a city (Glaeser, Kallal, Scheinkman, and Shleifer, 1992) and education levels (Acemoglu and Angrist, 1999; Moretti, 2004). Additional variables representing these alternative explanations are added to equation (2.6) to ensure of the robustness of the current findings. The results are shown in table (2.4). The main finding of this paper, the wage effect of shift in industrial compositions across cities, remains stable in size and highly significant at presence of such alternative mechanisms.

Glaeser et al. (1992) examine predictions of various theories of growth externalities (knowledge spillovers) within and between industries at city level in the U.S. during 1956 and 1987. They try to verify whether it is the geographic specialization or competition of geographically proximate industries that promote innovation spillovers and growth in those industries and cities. One measure of city growth they use is growth in wages. By testing empirically in which cities industry wages grow faster, as a function of geographic specialization and competition, they find that although specialization has no effects, diversity in a city helps wage growth of the industry. To control for such a mechanism, a measure of pre-trade (1991) industrial diversification in cities is introduced to equation (2.6), which is measured by one minus the Herfindahl index, or one minus the sum of squared sectoral employment shares in the city. The more diversified the industrial structure in a city, the lower should its Herfindahl index and the higher should this measure of industrial diversification be. If the finding of Glaeser et al. (1992) for the U.S. is valid in Brazil, a positive estimate of the coefficient of this variable is expected. The results are reported under columns OLS (1) and (2) and IV (1) and (2) in table (2.4), with the variable “diverse” representing such a mechanism.

The change in the measure of industrial composition is robust to introducing this alternative explanation for growth in wages at the city level. The measure of sectoral diversification is significant and positive both in OLS and after using instruments for $\Delta R_c$ and $\Delta ER_c$. In other words, cities that had a more diverse structure of employment – i.e., more equal employment shares across industries within a city – experienced higher growth rates in their industrial wages.

Note that introducing the measure of industrial diversity reduces the magnitude of the wage effects from changes in the measure of industrial composition, in the specification that controls for city level change in employment rate under OLS (1) and (2). Given the positive wage effects from these two variables, the reduction could be due to a positive correlation between the two
measures if the cities that experience shifts in composition toward higher paying industries were the ones that had more diversified industrial structure in 1991. Figure (2.13) illustrates the relationship between the two variables. It appears that the positive relationship between the two is driven by a few observations on the left tale of the diversification measure, with values less than 0.85. All of these cities are located in the Southeastern and Southern states of São Paulo and Santa Catarina, at very close distance to both Argentina and some of the most major commercial sea ports in Brazil. A close look into the change in the local compositions of employment in these cities in figure (2.14) reveals that, with no exception, these cities were all highly specialized in manufacturing in 1991 and during the years after trade liberalization experienced major declines in the share of manufacturing (as well as some other high paying industries). At the same time they experienced substantial increase in the share of agriculture, the second lowest-paying industry.

Moretti (2004) examines wages in U.S. cities in the 1980’s and finds that cities with greater increase in the proportion of workers with a BA or higher education have higher wage gains. Acemoglu and Angrist (1999) find weaker results for the impact of education using average years of education in a state. Here, it is already controlled for the level of education in estimating the sectoral wage premia and therefore, the measure of industrial compositions does not reflect cities with higher wages due to having higher levels education. However, both measures of education discussed in the two studies mentioned above are again controlled for here. One measure is the change in the proportion of workers with at least a university degree and the other is the changes in average years of schooling in city. Since the results of introducing these variables were similar, only those of controlling for the change in average years of schooling in cities ($\Delta schlyr_c$) are reported here. The results are shown under columns OLS (2) and IV (2) in table (2.4), where the change in average education is instrumented for by the 1991 levels of average education in cities. The change in the measure of industrial composition is robust to introduction of these variables. Neither of the two measures of city education is significant, which is closer to the results in Acemoglu and Angrist (1999).

As discussed in the Chapter 1 at the end of the section dedicated to robustness checks, it is expected that prevalence of rural-urban migration to make the estimates here more conservative. Given that the identification strategy relies on variations across cities, the main concern here is about the effect of rural-urban migration between cities on their sectoral compositions of employment. Migration from rural areas of a local labour market to the urban areas of another
local labour market due to higher growth rates in wages in the destination should in the destination result in higher employment shares for sectors that are more of a fit for low-skill workers, which relatively have lower innate wage premia, and lower employment shares in similar industries at the origin. Therefore, this pattern of migration should decrease the measure of industrial composition in the fast-growth labour markets (destinations) and increase it in slow-growth ones (origins), generating an inverse relationship between the measure of industrial composition and wages across cities. This should dampen the estimate of the general equilibrium wage effects of shifts in industrial composition here since the idea is that cities undergoing a change in their mix of industries in favour of high-premium industries should experience higher average wages. Therefore, if anything, prevalence of rural-urban migration make the estimates here to be more conservative.

2.6 Conclusion

It was asked here that whether the effect of trade liberalization on wages is limited only to its effect on demand for labour within the impacted industries or that the induced shifts in the composition of the overall demand also matters. Building on the theoretical model devised in Beaudry, Green, and Sand (2011) and using Brazilian household census data for years 1991 and 2000, it was found that trade-induced changes in industrial composition of the overall demand for labour across Brazilian cities had substantial impact of local wages in the cities.

Industrial composition of employment is measured as local employment-share weighted sum of national industry wage premia. Essentially, the estimates here indicate a long-run causal wage elasticity of about 3 with respect to local industrial composition due to general equilibrium effects. Cities’ distances from major commercial Brazilian sea ports as well as Argentina-Brazil border crossings were used as indicators of distributive effects of trade liberalization on compositions of employment across Brazilian cities. These distances were used to construct instrumental variables that help identify the trade-induced variation in compositions of employment across cities. The distance-based instruments explain about than 80% of the variation in the change in local compositions of employment, 27% of the variation in the change in city-level employment rates, and 70% of the variation in the change in city-industry-level employment rates across cities in Brazil during the 1990s. It was shown that the results do not suffer from endogeneity or sample selection bias and are robust to controlling for other
mechanisms in the literature that may explain the pattern of growth in industrial wages across cities.

Major changes in national trade or industrial policy are frequent in the less developed countries with already non-uniform distribution of economic development across regions, and can create geographic winners and losers depending on distribution of induced effects across space. The findings here are especially important in the context of these countries, where alleviation of poverty and geographically balanced distribution of purchasing power are on top of priorities.

Chapter 1 studied wage effects of shifts in local composition of employment across Mexican cities in the aftermath of Mexico joining NAFTA. It was shown that differences in trade-induced shifts in composition of employment among some southern Mexican cities, the historically poor region in Mexico and far away from Mexico-U.S. border, with the rest of regions after Mexico joined the NAFTA, substantially contributed to the worsening of North-South wage gap in Mexico (see Chiquiar, 2005; Chiquiar & Hanson, 2007; Hanson 1998, 2003, 2005a, 2005b) due to adverse wage effects of movement away from high-paying industries in the South. Both of these aspects are essentially important in the context of developing countries, given that they are relatively more prone to major policy changes as such and that spatially even provision of economic development or of their top priorities.

In the case of Brazil, the pattern of shifts in local industrial compositions in fact helped reduce the regional wage gap between the poor and rich areas in this country. As figures (2.1) to (2.10) illustrate, local industrial wages (averaged across cities and industries) in the historically poorest region of Brazil\(^57\) (see figure 2.4) in the North-East, increased more than any other region\(^58\) during 1991-2000. However, as it appears from figures (2.6) to (2.7), it was not due to exceptional shifts in compositions of local employment in cities in this region in favour of high paying industries. Rather, it was mostly due to adverse shifts (toward low-paying industries) in local compositions of employment everywhere else in the country. As illustrated in figure (2.8), the measure of industrial composition, averaged across cities within regions, declined substantially lower in the North-East region than all other regions but the Midwest. The Midwest

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\(^{57}\) A World Bank report calls the Northeast region the region with the “... most remaining income poverty ...” in Brazil (World Bank, 2001, p. 1). In a study on the evolution of the regional GDP’s in Brazil for the 1939-1998 period, Mossi et al. (2003) identify two spatial clusters in the country: a low-income one in the Northeast and a high-income one in the Southeast. Per capita income in São Paulo, the wealthiest Brazilian state, was 7.2 times that of Piauí, the poorest North Eastern state (Lall et al., 2004).

\(^{58}\) See figure (2.1) for the Regional Map of Brazil.
is relatively far from major commercial Argentina-Brazil border-crossings relative to the South and Southeast regions, and is far away from all the major commercial sea ports. As a result, trade liberalization affected the composition of cities in this region the least. This is while cities in the South and Southeast, being the historic manufacturing hubs in Brazil (see figure 2.6) and close to both Argentina and many major commercial sea ports (see figure 2.1), were quite adversely hit by the change in trade policy and experienced major declines in their measures of industrial compositions as a result.

The importance of a spatially balanced economic development accentuate the need for policy-analysis approaches that take into account such general equilibrium effects and address spatial heterogeneity of policy impacts across regions and localities.
### Table (2.1) – OLS and IV Estimation Results of Equation (2.6)

<table>
<thead>
<tr>
<th>Dependent Variable: $\Delta w_{ci}$</th>
<th>OLS</th>
<th>Selection Corrected OLS</th>
<th>IV</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>(1)</td>
<td>(2)</td>
<td>(1)</td>
</tr>
<tr>
<td>$\Delta R_c$</td>
<td>2.23*** (0.82)</td>
<td>2.19*** (0.78)</td>
<td>2.77*** (0.93)</td>
</tr>
<tr>
<td>$\Delta ER_c$</td>
<td>0.61 (0.44)</td>
<td>0.56 (0.43)</td>
<td>1.54 (1.20)</td>
</tr>
<tr>
<td>$\Delta ER_{ci}$</td>
<td>0.84*** (0.28)</td>
<td>0.81*** (0.28)</td>
<td>1.02*** (0.34)</td>
</tr>
</tbody>
</table>

| Industry Fixed Effects ($d_i$)     | Yes | Yes | Yes | Yes |
| Corrected for Sample Selection     | No  | No  | Yes | Yes |
| Obs.                               | 1839 | 1839 | 1839 | 1839 |
| $R^2$                              | 0.11 | 0.10 | 0.10 | 0.10 |

1º-Stage Statistics

<table>
<thead>
<tr>
<th>Over-id Test P-value</th>
<th>0.78</th>
<th>0.73</th>
</tr>
</thead>
<tbody>
<tr>
<td>Partial $R^2$ of</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Excluded Instruments ($\Delta R_c$)</td>
<td>0.81</td>
<td>0.80</td>
</tr>
<tr>
<td>F-state ($\Delta R_c$)</td>
<td>172</td>
<td>162</td>
</tr>
<tr>
<td>P-value ($\Delta R_c$)</td>
<td>0.00</td>
<td>0.00</td>
</tr>
</tbody>
</table>

| Partial $R^2$ of     | 0.27 |
| Excluded Instruments ($\Delta ER_c$) |      |
| F-state ($\Delta ER_c$) | 14.8 |
| P-value ($\Delta ER_c$) | 0.00 |

| Partial $R^2$ of     | 0.70 |
| Excluded Instruments ($\Delta ER_{ci}$) |      |
| F-state ($\Delta ER_{ci}$) | 173  |
| P-value ($\Delta ER_{ci}$) | 0.00 |

(•) Robust, city-clustered standard deviation. *, **, ***: Respectively, significance at 10%, 5%, and 1% levels of significance. **OLS (1): OLS estimation results of equation (2.6) controlling for the change in city employment rate. **OLS (2): OLS estimation results of equation (2.6) controlling for the change in city-sector employment rates. **IV (1): IV estimation results associated with the specification under Selection Corrected OLS (1) and using $IV^{\Delta \eta}$, $IV^{\Delta w}$, and $IV^{ER}$ as excluded instruments. **IV (2): IV estimation results of the specification under Selection Corrected OLS (2), using $IV^{\Delta \eta}$, $IV^{\Delta w}$, and $IV^{ER}$ as excluded instruments. ♣: Squared-partial correlation between excluded instruments and the endogenous variable in the associated first stage regression. ♥: The test is for the excluded instruments and is robust to clustering and heteroskedasticity.
Table (2.2) – Decomposing $\Delta R_{ct} = \Delta R_{ct}^{\Delta \eta} + \Delta R_{ct}^{\Delta w}$

<table>
<thead>
<tr>
<th>Dependent Variable: $\Delta w_{ct}$</th>
<th>OLS</th>
<th>IV</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>(1)</td>
<td>(2)</td>
</tr>
<tr>
<td>$\Delta R_{ct}^{\Delta \eta}$</td>
<td>2.28**</td>
<td>2.24**</td>
</tr>
<tr>
<td></td>
<td>(1.01)</td>
<td>(1.01)</td>
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<tr>
<td>$\Delta R_{ct}^{\Delta w}$</td>
<td>1.78</td>
<td>1.63</td>
</tr>
<tr>
<td></td>
<td>(2.31)</td>
<td>(2.31)</td>
</tr>
<tr>
<td>$\Delta ER_{ct}$</td>
<td>0.56</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.43)</td>
<td></td>
</tr>
<tr>
<td>$\Delta ER_{ct}$</td>
<td>0.81</td>
<td>0.83</td>
</tr>
<tr>
<td></td>
<td>(0.28)</td>
<td></td>
</tr>
</tbody>
</table>

Industry Fixed Effects ($d_i$) | Yes | Yes | Yes | Yes |
Corrected for Sample Selection | Yes | Yes | Yes | Yes |
Obs. | 1839 | 1839 | 1839 | 1839 |
$R^2$ | 0.10 | 0.10 | 0.10 | 0.10 |
P-value of the Test if: Coef. on $\Delta R_{ct}^{\Delta \eta} = $ Coef. on $\Delta R_{ct}^{\Delta w}$ | 0.86 | 0.83 | 0.80 | 0.73 |

1st-Stage Statistics

<table>
<thead>
<tr>
<th></th>
<th>(1)</th>
<th>(2)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Partial $R^2$ of Excluded Instruments ($\Delta R_{ct}^{\Delta \eta}$)</td>
<td>0.71</td>
<td>0.69</td>
</tr>
<tr>
<td>F-stat ($\Delta R_{ct}^{\Delta \eta}$)</td>
<td>85.0</td>
<td>78.0</td>
</tr>
<tr>
<td>P-value ($\Delta R_{ct}^{\Delta \eta}$)</td>
<td>0.00</td>
<td>0.00</td>
</tr>
<tr>
<td>Partial $R^2$ of Excluded Instruments ($\Delta R_{ct}^{\Delta w}$)</td>
<td>0.94</td>
<td>0.93</td>
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<tr>
<td>F-stat ($\Delta R_{ct}^{\Delta w}$)</td>
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<td>624</td>
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<tr>
<td>P-value ($\Delta R_{ct}^{\Delta w}$)</td>
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<td>0.00</td>
</tr>
<tr>
<td>Partial $R^2$ of Excluded Instruments ($\Delta ER_{ct}$)</td>
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<td></td>
</tr>
<tr>
<td>F-stat ($\Delta ER_{ct}$)</td>
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<td></td>
</tr>
<tr>
<td>P-value ($\Delta ER_{ct}$)</td>
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<td></td>
</tr>
<tr>
<td>Partial $R^2$ of Excluded Instruments ($\Delta ER_{ct}$)</td>
<td>0.70</td>
<td></td>
</tr>
<tr>
<td>F-stat ($\Delta ER_{ct}$)</td>
<td>173</td>
<td></td>
</tr>
<tr>
<td>P-value ($\Delta ER_{ct}$)</td>
<td>0.00</td>
<td></td>
</tr>
</tbody>
</table>

(): Robust, city-clustered standard deviation. *, **, ***: Respectively, significance at 10%, 5%, and 1% levels of significance. OLS (1): OLS estimation results of equation (2.6) controlling for the change in city employment rate rather and with decomposed change in industrial composition. OLS (2): OLS estimation results of equation (2.6) controlling for the change in city-sector employment rates and with decomposed change in industrial composition. IV (1): IV estimation results associated with the specification under Selection Corrected OLS (1) and using $IV^{\Delta \eta}$, $IV^{\Delta w}$, and $IV^{ER}_{ct}$ as excluded instruments. IV (2): IV estimation results of the specification under Selection Corrected OLS (2), using $IV^{\Delta \eta}$, $IV^{\Delta w}$, and $IV^{ER}_{ct}$ as excluded instruments. ♣: Squared-partial correlation between excluded instruments and the associated left-hand-side first-stage variable. ♥: The test is for the excluded instruments and is robust to clustering and heteroskedasticity.
### Table (2.3) – OLS and IV Estimation Results of Reflection Equation (2.23)

<table>
<thead>
<tr>
<th>Dependent Variable: $\Delta w_{ci}$</th>
<th>OLS</th>
<th>Selection Corrected OLS</th>
<th>IV</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>(1)</td>
<td>(2)</td>
<td>(1)</td>
</tr>
<tr>
<td>$\Delta W_c$</td>
<td>0.90***</td>
<td>0.88***</td>
<td>0.89***</td>
</tr>
<tr>
<td></td>
<td>(0.02)</td>
<td>(0.02)</td>
<td>(0.03)</td>
</tr>
<tr>
<td>$\Delta ER_c$</td>
<td>-0.21***</td>
<td>0.44**</td>
<td>-0.21***</td>
</tr>
<tr>
<td></td>
<td>(0.07)</td>
<td>(0.23)</td>
<td>(0.07)</td>
</tr>
<tr>
<td>$\Delta ER_{ci}$</td>
<td>0.44***</td>
<td>0.74***</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.23)</td>
<td>(0.27)</td>
<td></td>
</tr>
</tbody>
</table>

Industry Fixed Effects: Yes
Corrected for Sample Selection: Yes
Obs.: 1839
$R^2$: 0.53

**1st-Stage Statistics**

<table>
<thead>
<tr>
<th>Test</th>
<th>(1)</th>
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<tr>
<td>Over-id Test P-value</td>
<td>0.49</td>
<td>0.42</td>
</tr>
<tr>
<td>Endogeneity Test P-value ($\Delta W_c$)</td>
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<td>0.00</td>
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<tr>
<td>Partial $R^2$ of Excluded Instruments ($\Delta W_c$)</td>
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<td>0.20</td>
</tr>
<tr>
<td>F-state ($\Delta W_c$)</td>
<td>7.60</td>
<td>8.08</td>
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<tr>
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<td>0.00</td>
</tr>
<tr>
<td>Partial $R^2$ of Excluded Instruments ($\Delta ER_c$)</td>
<td>0.27</td>
<td></td>
</tr>
<tr>
<td>F-state ($\Delta ER_c$)</td>
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<td></td>
</tr>
<tr>
<td>P-value ($\Delta ER_c$)</td>
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</tr>
<tr>
<td>Partial $R^2$ of Excluded Instruments ($\Delta ER_{ci}$)</td>
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</tr>
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<td>F-state ($\Delta ER_{ci}$)</td>
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</tr>
<tr>
<td>P-value ($\Delta ER_{ci}$)</td>
<td>0.00</td>
<td></td>
</tr>
</tbody>
</table>

( ): Robust, city-clustered standard deviation. *, **, ***: Respectively, significance at 10%, 5%, and 1% levels of significance. OLS (1): OLS estimation results of equation (2.23) controlling for the change in city employment rate. OLS (2): OLS estimation results of equation (2.23) controlling for the change in city-sector employment rates. IV (1): IV estimation results associated with the specification under Selection Corrected OLS (1) and using $IV^{\Delta \eta}$, $IV^{\Delta w}$, and $IV^{\Delta \eta_{ci}}$ as excluded instruments. IV (2): IV estimation results of the specification under Selection Corrected OLS (2), using $IV^{\Delta \eta}$, $IV^{\Delta w}$, and $IV^{\Delta \eta_{ci}}$ as excluded instruments. ♣: Squared-partial correlation between excluded instruments and the endogenous variable in the associated first stage regression. ♥: The test is for the excluded instruments and robust to clustering and heteroskedasticity.
Table (2.4) – Robustness

<table>
<thead>
<tr>
<th>Dependent Variable: $\Delta w_{ct}$</th>
<th>City’s Pre-trade Industrial Diversification</th>
<th>Change in City’s Average Education (Years of Schooling)</th>
</tr>
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<tr>
<td>OLS</td>
<td>IV</td>
<td>OLS</td>
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<tr>
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<td>(3)</td>
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<tr>
<td>$\Delta R_c$</td>
<td>1.43*</td>
<td>2.45***</td>
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<tr>
<td>(0.73)</td>
<td>(0.73)</td>
<td>(0.73)</td>
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<tr>
<td>$\Delta ER_c$</td>
<td>0.67</td>
<td>0.37</td>
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<tr>
<td>(0.39)</td>
<td>(0.39)</td>
<td>(0.40)</td>
</tr>
<tr>
<td>$\Delta ER_{ct}$</td>
<td>0.68**</td>
<td>0.81**</td>
</tr>
<tr>
<td>(0.27)</td>
<td>(0.27)</td>
<td>(0.27)</td>
</tr>
<tr>
<td>diverse$_c$</td>
<td>1.01***</td>
<td>0.96***</td>
</tr>
<tr>
<td>(0.30)</td>
<td>(0.29)</td>
<td>(0.32)</td>
</tr>
<tr>
<td>$\Delta schy_r_c$</td>
<td>-0.14***</td>
<td>-0.15***</td>
</tr>
<tr>
<td></td>
<td>(0.04)</td>
<td>(0.04)</td>
</tr>
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</table>

Industry Fixed Effects ($d_i$)       Yes   Yes       Yes   Yes       Yes   Yes       Yes   Yes
Corrected for Selection              Yes   Yes       Yes   Yes       Yes   Yes       Yes   Yes
Instrumented for Alternative Mechanism No   No        Yes   Yes       Yes   Yes
Obs.                                 1839  1839     1839  1839     1839  1839     1839  1839
$R^2$                                 0.14  0.15     0.15  0.15

(...): Robust, city-clustered standard deviation. * , ** , *** : Respectively, significance at 10%, 5%, and 1% levels of significance.
Figure (2.1) – Map of Major Commercial Seaports in Brazil

(∗ indicates the top 15 major commercial seaports used as reference in this paper

These major ports are: Port Santos (Santos - SP), Port Vitória (Vitória - ES), Port Paranaguá (Paranaguá - PR), Port Itaguaí (Itaguaí - RJ), Port Rio Grande (Rio Grande - RS), Port Rio de Janeiro (Rio de Janeiro - RJ), Port Itajaí (Itajaí - SC), Port Itaqui (São Luís - MA), Port São Sebastião (São Sebastião - SP), Port São Francisco do Sul (São Francisco do Sul - SC), Port Aratu (Candeias - BA), Port Manaus (Manaus - AM), Port Suape (Ipojuca - PE), Port Pecém (São Gonçalo do Amarante - CE), Port Ilhéus (Ilhéus - BA).

Figure (2.2) – Map of Regions in Brazil
Figure (2.3) – Brazil’s Major Trade Partners
Figure (2.4) – Extreme Poverty Rate by Region in Brazil

Figure (2.5) – Industry Wage Premia in Brazil, 1991-2000 (Percentage difference from the base industry)
Figure (2.6) – Employment Share of Industries in Brazil by Regions
(Industries sorted by average national wage premia increasing left to right)
Figure (2.7) – Change in Employment Share of Industries in Brazil by Region, 1991-2000
(Industries sorted by average national wage premia increasing left to right)
Figure (2.8) – Change in the Measure of Industrial Composition in Brazil by Region
Figure (2.9) – Change in Local Industrial Wages in Brazil, Averaged across Cities within the Region, 1991-2000
(Industries sorted by average national wage premia increasing left to right)
Figure (2.10) – Change in Local Industrial Wages in Brazil by Region, 1991-2000
(Averaged across Cities and Industries within the Region)
Figure (2.11) – Illustration of 123 Distinct Labour Markets (Metropolitan Areas) in Brazil

Figure (2.12) – Controlled Variation in the Change in Local Industrial Wages vs. Controlled Variation in the Change in the Measure of Local Industrial Composition

\[ \text{coef} = 2.23, \text{ (robust) se} = .82, t = 2.71 \]
Figure (2.13) – Industrial Diversification in Cities Composition of Employment in 1991 vs. Change in the Measure of Industrial Composition 1991-2000

The scatter plot shows the relationship between the change in the measure of local industrial composition and industrial diversification in city in 1991 (1 - Herfindahl Index). The line of best fit indicates a positive correlation, with a coefficient of determination (coef) of 0.16. The robust standard error (se) is 0.03, and the t-statistic is 4.97.
Figure (2.14) – 1991-Composition of Employment and Change in Composition of Employment, Averaged across Cities with 1991-Measure of Industrial Diversification Lower than 0.85 (%, 1991-2000, Industries sorted by average national wage premia increasing left to right)
Chapter 3

Wages as Primary Determinant of Self-Employment: The Case of Brazilian Cities, 1991-2000

3.1 Introduction

Not much is known about the reasons behind spatial differences in self-employment rate. While differences in local factors might matter, such factors are also impacted by changes in self-employment, raising concerns about identification. Therefore, exogenous variations in local factors are needed to be able to identify and evaluate the local determinants of self-employment rate.

How do structures of wages and employment affect reallocation to self-employment? To address this question, the multi-city, multi-industry search and bargaining model of a labour devised in Beaudry, Green, and Sand (2011) is expanded here to incorporate self-employment and understand how in a general equilibrium framework wages and employment rate relate to self-employment rate. Since a large part of the self-employment in Brazil is informal and own-account (see Fiess, Fugazza, and Maloney, 2010), self-employment is modeled here as an alternative to unemployment. The outcome of this model provides the structure needed in a proper empirical investigation of the question above and justifies the identification strategy.

The intuition behind the theoretical model devised here is simple. The decision of an unemployed worker to turn to self-employment, in principle, depends on a comparison between the expected value of self-employment net of the associated costs versus the expected value of remaining unemployed in the hope of future wage-employment. The latter is mainly affected by the likelihood of wage-employment and expected earnings from it. The expected earnings from employment is perceived from the average wage in the local economy, measured as the weighted sum of local sectoral wages with each industry’s share in local employment as the

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60 It is assumed here that labour is mobile within skill-groups across sectors within a local economy and that the chance of finding a job in a specific sector is proportional to that sector’s share in local employment.
weight. The likelihood of employment is perceived from the wage-employment rate. Therefore, self-employment rate is expected to inversely depend on the average wage and employment rate.

Building on the outcome of the theoretical model, the 1991 and 2000 waves of the Brazilian household census data are used here to identify the long-term, causal effects of local employment rate and wages on local self-employment rate across Brazilian sub-national labour markets, referred to as cities hereinafter. Variations across cities in terms of change in the structures of wages and employment allow for identifying their effects on local self-employment.

To address the concerns about endogeneity of local wages and employment rate in a general equilibrium setting and make sure of causality, exogenous variations across cities in terms of exposure to effects of trade liberalization and its impact on their local structures of wages and employment are used. As indicators of the transportation costs associated with each city, their distances from major commercial points of entry and exit in Brazil are used to explain the variation across cities in the extent of exposure to shocks from trade liberalization and its consequent impact on their local structures of wages and wage-employment. This approach is deemed effective since self-employment is unlikely to be directly determined by an exogenous, time-invariant variable as such determined by nature (Glaeser, Rosenthal, Strange, 2010), while the extent of trade shock penetration is known to depend on factors such as being close to a good harbor (Disdier & Head, 2008). Since trade liberalization can in principle directly impact self-employment rate in ways other than through structure of wages and employment (e.g., transfer of knowledge), the assumption here is that such effects are negligible as self-employment in Brazil mostly comprises own-account and informal self-employment as opposed to multiple-account and formal (see Fiess, Fugazza, and Maloney, 2010).

Research on determinants of self-employment has overlooked the effects of changes in wages on reallocation from unemployment to self-employment. The current study fills this gap. It is

\[ W_c = \sum_i \eta_{ic} w_{ic}, \]  
where \( \eta_{ic} \) is the wage-employment share of industry \( i \) in city \( c \) and \( w_{ic} \) is the wage that is innate to industry \( i \) in city \( c \).

IPUMS-International, a project in the Minnesota Population Centre Data Projects is to be highlighted as the provider of the data used in this study.

Socio-Economic data in Brazil is available for municipios, the main administrative level for local policy implementation and management, which due to strong economic links neighboring municipios cannot be considered as distinct labour market. They also vary dramatically in size and over time in boundaries. To properly define labour markets for the purpose of empirical analysis, this study adapts a grouping of municipios into 123 cities/metropolitan areas according to a comprehensive study by the Government of Brazil on characterization and trends of urban network in Brazil (IPEA, IBGE, & UNICAMP, 2002).
shown here that self-employment rate causally, and inversely, depends on the local average wage and employment rate. Moreover, it is found that local self-employment rate is substantially more responsive to changes in local wages than employment rate. Given that the two variables do not necessarily move in the same direction in the long term, they can oppositely impact the self-employment rate. In fact, as shown here, this is what happened in Brazil across cities during the 1990s; while in average the local average wages increased during this period, local employment rates declined, as a result of which self-employment rates also declined in average but by a small amounts.

Beaudry, Green, & Sand, (2011), and chapters 1 and 2 above show that shifts in industrial composition of local employment substantially impact local sectoral wages, so that local industrial wages rise in all sectors as the composition of employment shifts toward relatively higher paying industries.\textsuperscript{64} It is found here that through such wage effects, shifts in industrial composition of local employment substantially affect local self-employment rate. Therefore, differences across space in the pattern of change in industrial composition can explain the spatial differences in self-employment rate.

The robustness of the results is tested by including the alternative mechanisms proposed in the literature that help explain differences in the self-employment rate across space. Glaeser (2007) finds that area level age and education are important determinants of self-employment rate which explain fifty percent of its variation across cities. Changes in the cities’ demographic attributes, including average age and education are included here to control for such effects. A vast literature has shown a relationship between agglomeration and innovation (Glaeser, Kallal, Scheinkman, and Shleifer, 1992; Agrawal, Kapur, & McHale, 2008; Simonen & McCann, 2008; Gerlach, Ronde, & Stahl, 2009; Agrawal, Cockburn, & Rosell, 2010; Glaeser, Kerr, & Ponzetto, 2009). A measure of industrial diversification\textsuperscript{65} in each city is used to control for agglomeration versus competition effects in cities. Also, instead of using the whole sample, as a robustness check different cuts of the sample are considered to include only men, non-agriculture, or the

\textsuperscript{64} Beaudry, Green, and Sand (2011) show how shifts in industrial composition that favour higher paying industries increase wages in all industries in an economy by improving the bargaining position of unemployed workers through higher chances of employment in higher-paying industries. They find such a mechanism to have substantially affected the wage structure in the US during 1980-2000. Building on their work, Chapters 1 and 2 find similar substantial general equilibrium wage spillover effects caused by shifts in industrial compositions in cities of Mexico and Brazil that were induced by changes in trade policies in these countries during the 1990s.

\textsuperscript{65} Specifically, one minus the Herfindahl Index (the sum of squared shares of each industry) for each city.
fulltime wage- and self-employed. Overall, the results are shown to be robust to all these changes.

Identifying the local determinants of self-employment such as local structures of wages and employment are important for various reasons. A considerable portion of self-employment in developing countries is in the form of informal employment, which is often characterized by inferior jobs and lack of security and its expansion is seen to have negative influences on welfare (Stallings & Peres, 2002). Also, expansion of self-employment possibly involves a rise in entrepreneurship and formation of new start-ups, which are seen as the engines of economic growth and job creation (Smith, 1776; Marshal, 1890; Schumpeter, 1934; Kirzner, 1973; Glaeser, Kallal, Scheinkman, & Shleifer, 1992; Weitzman, 1996; Glaeser, 2007). Establishing the link between local structure of wages and wage-employment and local self-employment rate can also help explain spatial differences in local self-employment rate. Furthermore, this seems to be a first step in a structural analysis and evaluation of the impact of policy changes such as trade liberalization on self-employment.

The layout of the paper is as follows. Section 3.2 briefly discusses the trends in self-employment in Brazil during the 1990s. Section 3.3 reviews the change in Brazilian trade policy and describes the changes in foreign trade structure in this country after trade liberalization. Section 3.4 discusses the theoretic basis. Section 3.5 describes the identification strategy. Section 3.6 describes the instruments. Section 3.7 explains the data used here. Section 3.8 reports the estimation results and section 3.9 concludes the paper. Some of the important technical details are presented in the appendix.

3.2 Self-Employment in Brazil

There is substantial variation across cities in Brazil during the 1990s insofar as the change in self-employment rate is concerned. According to the Brazilian household census data for years 1991 and 2000, the change in self-employment rate across 123 Brazilian cities used in this study during the 1990s ranges from a low of -37% to a high of 18%, giving rise to a simple mean of 9% and a standard deviation of 10.1 percentage points. Average self-employment rate across cities decreased from 16% in 1991 to 14% in 2000.

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66 The ratio of the self-employed workers to working-age population in a city.
67 See footnote 32.
3.3 Trade Liberalization in Brazil

Brazil underwent substantial trade liberalization during the 1990s and opened its economy to foreign competition. While this shift in trade policy is considered to have played an important role in recent economic transformation of Brazil (Hay, 2001; Muendler, 2002; Pavcnik, Blom, Goldberg, & Schady, 2002; The Economist, 2009), some of its impacts have seldom been closely studied. One such understudied facet of the Brazilian trade liberalization is its impact on reallocation to self-employment.

From 1988 to 1994, Brazil gradually liberalized its trade regime and reduced its tariffs and non-tariff barriers to trade (NTBs) in several stages. During the first stage, in 1988 and 1989, the reforms reduced the average tariff levels from about 60 percent in 1987 to 39 percent in 1989 (Pavcnik, Blom, Goldberg, & Schady, 2002). Hay (2001) argues that the initial stage of tariff reductions did not significantly affect the exposure of domestic industries to increased foreign competition due to continuous reliance on substantial NTBs, which were eliminated in the second stage of the reforms that started in 1990. From 1990 to 1994 the average tariff were lowered from 34% in 1990 to 11% in 1995. These reforms were partially reversed in 1995 following the real appreciation of the Real that lowered the competitiveness of the manufacturing sector and widened the current account deficit. Nevertheless, the average tariff climbed only slightly between 1995 and 1998. Overall, average manufacturing tariffs in Brazil declined from about 60% in 1987 to 15% in 1998 (Goldberg and Pavcnik, 2003).

Total merchandize export of Brazil increased by 74.4% from US$31.6 billion in 1991 to US$55.1 billion in 2000 and total merchandize import of Brazil increased by 97.0% from US$30.0 billion to US$59.1 billion. During this period, Brazil’s total export and import in manufacturing increased by 67.8% and 157%, respectively. The full enactment of the regional free trade agreement between Argentina, Brazil, Paraguay, and Uruguay (MERCOSUR) in 1995 falls in the middle of the horizon of this study. This agreement resulted in substantial increase in the importance of Argentina as a trade partner for Brazil (in terms of its share in total exports and imports of Brazil, which places it second only to the US). However, it was not the only change resulting from the shift in trade policy in Brazil during 1991-2000. As table (3.1)

---

68 Such as import licenses, special import programs, and administrative barriers to trade

69 UNCTAD Handbook of Statistics, 2009. (Calculated at current prices and current exchange exchange rates.)

70 MERCOSUR or the Common Market of the South was founded in 1991 and was fully enacted in 1995. For more information see www.mercosur.int.
reports, within manufacturing, Brazil’s imports from the US increased by 153% percent and its exports to the US increased by 102%. Respectively, the same statistics for Argentina are 313% and 305%, for Germany are 127% and 8.46% and, for Japan are 131% and -5.84%, for Italy are 170% and 30.1%, for France are 205% and 36.3%, for UK are 167% and 34.1%, and for China are 1,783% and 370%. 71

Such a boom in trade relations in the aftermath of trade liberalization in Brazil has substantially amplified the importance of access to foreign markets for its local economies. Other than Argentina, which shares a land border with Brazil in south, the rest of Brazil’s major trade partners are widespread across the oceans. This has made distance to the Argentina-Brazil border and major Brazilian commercial sea ports a key difference among cities in terms of their exposure to the trade boom and an important indicator of the geographic distribution of the impacts of change in trade policy across cities during this period.

Sea ports 72 handle 95% of Brazil’s trade by volume and 85% of its trade by value. This provides the rational for using distance from major commercial sea ports in Brazil as an indicator of how the effects of change in trade policy were distributed across different cities in Brazil. Furthermore, as a result of the MERCOSUR, Argentina’s share of total Brazilian Trade increased significantly during the 1990s. Within manufacturing the US, France, Germany, Italy, UK, Japan, and China together imported 52% and 48% of Brazil’s exports and exported 47% and 48% of Brazil’s imports, respectively in 1991 and 2000, with the US alone having an average share of 22% and 23% in Brazil’s exports and imports in this period. This is while Argentina increased its share in Brazil’s exports and imports to 10.1% and 12.2% in 2000. 73

3.4 Theory

In this section a general equilibrium search and bargaining model of a labour market is devised that builds on the model used in Beaudry et. al (2011) to incorporate self-employment. Self-employment in the context of developing countries is mostly seen as informal employment than entrepreneurship (see Fiess, Fugazza, and Maloney, 2010). For this reason, self-employment is modeled here as a costly alternative to unemployment with a net benefit that is larger than

72 See figure (3.2) for a map of the major Brazilian sea ports.
73 Ibid.
unemployment benefits at low levels of self-employment, decreases in self-employment rate\(^{74}\), and depends on city level cost advantages in self-employment. This model is essentially helpful in understanding how in a city self-employment rate depends on employment rate and average wage (local industrial wages and composition of employment) and helps to make sense of the endogeneity of variables and direction of bias in the empirics. The outcome of the model guides the empirics and justifies the identification strategy.

In this model, there are \( C \) local economies, referred to as cities, each having its local employment spread over \( I \) industries. Each industry has a unique product, which can be produced in any of the cities and whose price is given by \( P_i \). These industrial products are aggregated to a final good given by:

\[
Y = \left( \sum_{i=1}^{I} (a_i Z_i^X) \right)^{1/x}, \quad x < 1 \quad (3.1)
\]

whose price is normalized to one. In (3.1), differences in \( a_i \) capture the differences in demand across industries. The sum of local productions in each industry, \( Z_{ic} \)'s, across cities determine the total industry product, \( Z_i \).

Within each local industry firms must undergo a cost \( \theta_{ic} \) to create a vacancy, the value of which is endogenously determined in equilibrium. If a vacancy is filled, it generates a flow of profits for the firm given by:

\[
P_i - w_{ic} + \epsilon_{ic}
\]

where \( w_{ic} \) is the wage and \( \epsilon_{ic} \) is a city-industry specific cost, with \( \sum_c \epsilon_{ic} = 0 \). In a steady-state equilibrium, the discounted value of profits from a filled vacancy, \( V_{ic}^f \), and the discounted value of profits from a vacancy, \( V_{ic}^v \), should satisfy the following Bellman (dynamic programming) equations:

\(^{74}\) The underlying assumption here is a random heterogeneity across individuals in the ability to become self-employed, so that at first those with the highest draws of ability become self-employed and as more individuals become self-employed – i.e., as self-employment rises – individuals with lower draws of ability remain unemployed, for whom it is more difficult to become self-employed. For simplicity, and without loss of generality, I have not modeled the probability distribution function of the individual self-employment ability.
\[ \rho V_{i}^{f} = p_{i} - w_{ic} + \epsilon_{ic} + \delta^{we}(V_{i}^{u} - V_{i}^{f}) \]  
\[ \rho V_{i}^{w} = -r_{i} + \psi_{c}(V_{i}^{f} - V_{i}^{w}) \]  

were, \( \psi_{c} \) denotes the endogenous probability a firm will fill a vacancy and \( r_{i} \) is the cost of maintaining a vacancy. Without loss of generality \( r_{i} \) is set to zero. \( \delta^{we} \) denotes the exogenous death rate of jobs.

An unemployed worker finds employment opportunities at an endogenous probability \( q_{c} \) or can choose to become self-employed at an exogenous probability \( \phi \). Self-employment is chosen over unemployment if the continuation value of self-employment, \( U_{c}^{se} \), minus the cost of becoming self-employed, \( \theta_{c}^{se} \), is higher than the continuation value of remaining unemployed, \( U_{c}^{u} \). Self-employment generates a flow of utility denoted by \( k + \xi_{c}^{se} \), where \( \xi_{c}^{se} \) captures city-specific advantages in self-employment. The cost of becoming self-employed is also endogenously determined in equilibrium. Unemployed workers receive flow unemployment benefits \( b \). For simplicity, and without loss of generality, it is assumed that unemployed workers are perfectly mobile across industries within a city; i.e., within an skill-group the unemployed workers can find a job in any local industry.\(^{75}\) Denoting the value of employment with \( U_{i}^{we} \), the following Bellman equations should be satisfied:

\[ \rho U_{i}^{we} = w_{ic} + \delta^{we}(U_{c}^{u} - U_{i}^{we}) \]  
\[ \rho U_{c}^{se} = k + \xi_{c}^{se} + \delta^{se}(U_{c}^{u} - U_{c}^{se}) \]  
\[ \rho U_{c}^{u} = b + q_{c} \left( \sum_{j} \eta_{jc}U_{j}^{we} - U_{c}^{u} \right) + \phi(\text{Max}\{U_{c}^{se} - U_{c}^{u} - \theta_{c}^{se}, 0\}) \]  

\(^{75}\) Mobility across cities is ruled out. It can be shown however that adding some mobility across cities does not affect the outcome of the model, because prices of city level amenities, such as the price of housing, will rise and bring cross-city migration to a halt before all the wage differences across cities within industries get washed away. For more details, see Beaudry et al. (2011).
The instantaneous probability of wage-employment in a specific industry is assumed to be proportional to the relative size of the industry in local economy, indicated by $\varphi_c \eta_{jc}$; $\eta_{jc}$ is the share of industry $j$ in total number of jobs in city $c$. To be able to explicitly solve the model in a way that can guide the empirical exploration, it is assumed here that only unemployed workers can search for jobs or switch to self-employment.

When a match between a firm and an unemployed worker takes place, they bargain a wage, which, without loss of generality, is assumed to be set according to the following rule:

$$V_{ic}^f - V_{ic}^w = U_{ic}^{we} - U_{ic}^u. \quad (3.7)$$

The probability a match is made is determined by a Cobb-Douglas matching function:

$$M\left((L_c - S_c - E_c), (N_c - E_c)\right) = (L_c - S_c - E_c)^\sigma (N_c - E_c)^{1-\sigma}, \quad (3.8)$$

where $L_c$ indicates the size of labour force, $S_c$ is the number of the self-employed, $E_c$ denotes the number of the wage-employed, and $N_c (=\sum_i N_{ic})$ is the total number of jobs in city $c$. Given the exogenous death rate of wage-employment, $\delta^{we}$, the steady-state equilibrium is given by the following:

$$\delta^{we} ER_c = M\left((1 - ER_c), \left(N_c \cdot \frac{1}{1 - SR_c} - ER_c\right)\right)$$

$$= (1 - ER_c)^\sigma \left(N_c \cdot \frac{1}{1 - SR_c} - ER_c\right)^{1-\sigma} \quad (3.9)$$

and

$$U_c^{se} - U_c^u = \theta_c^{se} (SR_c). \quad (3.10)$$

In these equations $ER_c = \frac{E_c}{L_c - S_c}$ and $SR_c = \frac{S_c}{L_c}$ are the local wage-employment rate and self-employment rate, respectively. In order to have unemployment in equilibrium, it is assumed that
cost of self-employment is increasing in the self-employment rate \( \frac{\partial \theta^e \sigma (SR_c)}{\partial SR_c} > 0 \). \( \theta^e \) should be viewed as the marginal cost of self-employment.

The number of jobs created in industry \( i \) in city \( c \), \( N_{ic} \), is determined by the free entry condition:

\[
V_{ic}^p = \theta_{ic} \left( \frac{N_{ic}}{L_c} \right)
\]

(3.11)

where \( \theta_{ic} \) is the cost of creating the marginal job. In order to avoid the concentration of employment in only one industry within cities, \( \theta_{ic} \) is assumed to be increasing in the number of new jobs being created locally in the industry.

Finally, the probability an unemployed worker finds employment (\( \varphi_c \)) and the probability a firm fills a vacancy (\( \psi_c \)) depend on wage-employment rate.

At the city level the market clearing prices of industrial outputs are taken as given and the equilibrium of the model is defined by values of \( w_{ic} \), \( N_{ic} \), \( ER_c \), and \( SR_c \) that satisfy conditions expressed in (3.7), (3.9), (3.10), and (3.11). The equilibrium of the model shows how a city takes advantage of industrial prices and its technological advantages to adjust its production mix, and how this affects the decision on self-employment. At the economy level, changes in demand for industrial products indicated by the \( a_i \)'s will determine the prices. The focus here is to understand how in a steady-state equilibrium wages, wage-employment rate, and self-employment rate relate to each other and respond to shifts in their exogenous driving forces, \( a_i \)'s, \( \epsilon_{ic} \)'s and \( \xi^e s \)'s, and.

Equations (3.9) and (3.11) define an important equilibrium relationship between the employment rates: to maintain the number of jobs in equilibrium, a rise in self-employment rate implies a rise in wage-employment rate, but at falling employment levels. Essentially, a sudden rise in self-employment means a decline in the frequency of search for wage-employment and a lower number of individuals searching for jobs. This means filling vacancies become costlier for firms especially that the lower number of unemployed workers puts an upward pressure on wages and makes the prospect of creating jobs less attractive (lower \( V_{ic}^p \)). The only way to maintain the equilibrium level of jobs is to have less employment, which implies lower employment rate and higher continuation value of creating vacancies. In other words, the model
predicts that after a sudden rise in self-employment rate, it is not clear how wage-employment rate changes; on the one hand it increases due to lower level of unemployment, on the other hand it declines as the level of employment declines.

### 3.4.1 Solving for Self-Employment Rate

Here the model is solved for the self-employment rate, treating wages and $\eta_{ic}$'s as given and leaving the discussion of their endogenous determination and their implications for later.

Using equations (3.4), (3.5), and (3.6) the following equation can be derived:

$$
(\rho + \delta^{se})(U^se_c - U^u_c) = k + \xi^{se}_c - \left(\frac{\rho + \delta^{we}}{\rho + \delta^{we} + \varphi_c}\right)b - \left(\frac{\varphi_c}{\rho + \delta^{we} + \varphi_c}\right)\sum_j \eta_{jc}w_{jc} \\
- \phi\left(\frac{\rho + \delta^{we}}{\rho + \delta^{we} + \varphi_c}\right)(\text{Max}\{U^se_c - U^u_c - \theta^{se}_c, 0\}) \quad (3.12)
$$

Notice that a change in wages or local composition of employment ($\eta_{jc}$'s) will in general affect the utility of self-employment. The composition matters because unemployed workers can find wage-employment in any local industry within their skill-group. Also, notice that wage-employment rate also matters, as it is implicitly hidden within $\varphi_c$.

Considering the equilibrium condition (3.10), (3.12) in equilibrium becomes:

$$
\theta^{se}_c(SR_c) = \alpha_{0c} + \alpha_{1c}W_c + \frac{1}{(\rho + \delta^{se})}\xi^{se}_c \quad (3.13)
$$

where $W_c = \sum_j \eta_{jc}w_{jc}, \alpha_{0c} = \frac{k}{(\rho + \delta^{se})} - \frac{(\rho + \delta^{we})}{(\rho + \delta^{we} + \varphi_c)(\rho + \delta^{se})}b, \alpha_{1c} = -\frac{\varphi_c}{(\rho + \delta^{se})(\rho + \delta^{we} + \varphi_c)}$. To move toward an equation amenable to empirical estimation and to express the role of wage-employment rate, a first-order linear approximation of (3.13) is considered around a point where there is no difference across cities in wage- and self-employment rate$^{76}$:

$$
SR_c = \alpha_0 + \alpha_1W_c + \alpha_2ER_c + \xi^{se}_c, \quad (3.14)
$$

$^{76}$ Which would be the case if $\epsilon_{ic} = 0$ and $\xi^{se}_c = 0$, for all $c$ and $i$. 

where $\alpha_1 < 0$, $\alpha_2 < 0$, and $\zeta^{se}_{ct} = \frac{1}{(\rho + \delta_{se})} \zeta^{se}_{ct}$. An empirical specification that closely follows (3.14) would be:

$$SR_{ct} = \alpha_0 + \alpha_1 W_{ct} + \alpha_2 ER_{ct} + \alpha_3 t + \alpha_4 c + \zeta^{se}_{ct}, \quad (3.15)$$

where the $t$ in the subscripts indicates the year and $\alpha_3 t$ denotes year-specific effects. Equation (3.15) differenced over time will be used as the baseline estimation equation:

$$\Delta SR_{ct} = \Delta \alpha_3 t + \alpha_1 \Delta W_{ct} + \alpha_2 \Delta ER_{ct} + \Delta \zeta^{se}_{ct}, \quad (3.16)$$

where $\Delta$ is the time-difference operator and $\Delta \alpha_3 t$ plays the role of an intercept as there are only two years of data used in this study. As discussed later, both the average wage and the wage-employment rate are likely to be endogenous.

### 3.4.2 Solving for Wages

Here the model is solved for wages, treating the employment rate and $\eta_{ic}$’s as given, leaving the discussion of their endogenous determination and its implications to later.

Using equations (3.2), (3.3), (3.4) and (3.6), and focusing on equilibrium conditions (3.7) and (3.10), the following solution for wages can be derived:

$$w_{ic} = \gamma_{c0} + \gamma_{c1} P_t + \gamma_{c2} \sum_j \eta_{jc} w_{jc} + \gamma_{c1} \epsilon_{ic}, \quad (3.17)$$

where $\gamma_{c0}$, $\gamma_{c1}$, and $\gamma_{c2}$ are all implicit functions of wage-employment rate. The term $\sum_j \eta_{jc} w_{jc}$ captures the weighted-average city wage, where local industrial employment shares ($\eta_{jc}$’s) are used as the weights.

This equation essentially indicates that in a search and bargaining framework wages act as strategic complements; a rise in one will increase all other wages through increasing the

---

77 See the appendix for more details.
average wage in city. The extent of complementarity is captured by \( \gamma_{c2} \), which is smaller than one. Essentially an initial increase in wages (or a shift in composition of employment in favour of locally high-wage industries) that increase the average wage by one unit, will increase all local wages by \( \gamma_{c2} \), which increases the average by the same amount, which according to (3.17) increase all local wages again by \( \gamma_{c2}^2 \), and so on and so forth. By the time a new equilibrium arises, the total effect would be equal to \( 1 + \frac{\gamma_{c2}}{1-\gamma_{c2}} \) (\( = 1 + \gamma_{c2} + \gamma_{c2}^2 + \cdots \)), where \( \frac{\gamma_{c2}}{1-\gamma_{c2}} \) captures the extent of the general equilibrium, inter-sectoral wage spillover. Given that the model indicates that \( \gamma_{c2} \) is smaller than one, the size of such general equilibrium wage spillovers could be quite large. For instance, an estimate of \( \gamma_{c2} = 0.8 \) gives rise to \( \frac{\gamma_{c2}}{1-\gamma_{c2}} = 4 \), which means that an initial increase in composition of employment that increases the average wage by one unit at constant wages, increases the average wage through general equilibrium effects by 4 units. If workers were not mobile across local industries within skill-group, this effect would disappear.

To explicitly specify the wage-employment rate, manipulation\(^{79}\) of equation (3.17) and then taking a first-order linear approximation\(^{80}\) of it would give the following wage equation:

\[
w_{ic} = d_i + \gamma_2 \frac{\sum_j \eta_{jc} (w_j - w_1)}{(1 - \gamma_2)} + \lambda_{ERC} + \varepsilon_{ic},
\]

(3.18)

where \( d_i \) captures industry level factors including industrial prices, \( \gamma_2 \) essentially captures the average of \( \gamma_{c2} \) across cities, \( w_j \) is the innate wage in industry \( j \) at the national level, and \( w_j - w_1 \) is the national level wage premium in industry \( j \) relative to industry \( 1 \), and \( \varepsilon_{ic} = \gamma_1 \varepsilon_{ic} + \gamma_1 \frac{\gamma_2}{(1-\gamma_2)} \sum_{j=1}^{I} \varepsilon_{jc} \).

Equation (3.18), shows how city-industry wages depend on the local employment rate and industrial composition of a city’s employments captured by the term \( \sum_j \eta_{jc} (w_j - w_1) \). From here on, this term is denoted by \( R_c \) and is referred to it as the measure of local industrial composition:

\(^{78}\) For more details see Manski (1993) and Moffitt (2001).

\(^{79}\) See the appendix for more details.

\(^{80}\) Around a point where cities all have the same industrial composition and employment rates, which would be the case if \( \varepsilon_{ic} = 0 \), for all \( c \) and \( i \).
Notice that a higher value for the measure of industrial composition indicates that the city’s employment has shifted in favour of the relatively higher paying sectors. Also, notice that the measure of industrial composition closely matches the structure of the average wage, but only uses national wage premia instead of local wages. This difference makes this measure to only capture the effect of shifts in local composition, as changes in local wages do not affect this measure.\(^{81}\)

Later, as part of the empirical estimation strategy, the change in the average wage in the baseline estimation equation, equation (3.16), is replaced using equation (3.18). It is useful to explain here how this is done. Multiplying both sides of (3.18) by \(\eta_{ic}\) and summing across industries give the following equation:

\[
\sum_i \eta_{jc} w_{ic} = \sum_i \eta_{jc} d_i + \beta \sum_j \eta_{jc} (w_j - w_1) + \lambda ER_c + \sum_i \eta_{jc} \varepsilon_{ic}, \quad (3.20)
\]

where \(\beta = \frac{\gamma_1}{1 - \gamma_2}\). Notice that in an empirical interpretation of equation (3.18), the term \(d_i\) can be replaced by a set of industry dummies which essentially capture the wage premium of industries relative to the base industry (here, industry 1) averaged across cities; i.e., \(d_i\) captures \((w_j - w_1)\). As a result the term \(\sum_i \eta_{jc} d_i\) in (3.20) is empirically not identifiable from the measure of industrial composition, \(\sum_j \eta_{jc} (w_j - w_1)\), in the same equation. Therefore, after putting the year subscripts and taking the time difference, (3.20) can be written as:

\[
\Delta W_{ct} = (1 + \beta) \Delta R_{ct} + \lambda \Delta ER_{ct} + \Delta \sum_i \eta_{jc} \varepsilon_{ict}, \quad (3.21)
\]

\(^{81}\) Note that the theory is silent about attributes of workers, and specifically their skills. One should think of the wages and wage premia as calculated for one skill group so that an increase in the measure of industrial composition is not an increase of skill. In the empirics these will be obtained controlling for skills and other attributes of the workers.
It is interesting to see that the coefficient of $\Delta R_{ct}, (1 + \beta)$, essentially captures the total wage effect of a shift in industrial composition that initially changes the average wage by 1 unit, and through general equilibrium, inter-sectoral wage spillover effects discussed above, increases all local wages and therefore the average wage by $\beta$. \textsuperscript{82} Equation (3.21) is later used to replace $\Delta W_{ct}$ in (3.16).

### 3.4.3 Endogeneity

At this point, there is enough structure to discuss the concerns about endogeneity in an empirical estimation of equation (3.16). To estimate this equation, variations across cities in the change in average wage and employment rate are explored to see whether they systematically vary with the change in self-employment rate within cities. The conditions under which OLS consistently estimates the parameters in (3.16) are:

\[
\lim_{c \to \infty} \sum_c \Delta W_c \Delta \xi^{se}_c = 0 \quad (3.22)
\]

\[
\lim_{c \to \infty} \sum_c \Delta ER_c \Delta \xi^{se}_c = 0. \quad (3.23)
\]

Consider a steady-state equilibrium of the model where there is a sudden rise in $\xi^{se}_c$, say due to a new government-sponsored program that promotes self-employment. As a result, on the margin some of the unemployed will switch to self-employment, which raises the self-employment rate. At given level of employment, the decline in unemployment by definition raises the wage-employment rate. It can be seen from equilibrium condition (3.9) that given the total number of jobs in the city, $N_c$, a higher self-employment rate implies an increase in wage-employment rate so to keep this condition in check at given level of employment. However, the rise in self-employment affects the tightness of the labour market at given number of jobs available in the city since it decreases the number of unemployed people who are searching for jobs. This means the bargaining position of the unemployed workers improves and will push wages upward across all industries within the city according to (3.18). At the same time, it means

\textsuperscript{82} Notice that $\gamma_2$ can be interpreted as the average of $\gamma_{ct}$ across cities.
it takes longer for firms to fill job vacancies. The rising employment rate and wages, thus, make the prospect of job creation grim as $V_c''$ declines. The declining value of vacancy affects the equilibrium condition (3.10). At the given level of $N_c$, to return to equilibrium, employment levels should decline so to raise $V_c''$ and satisfy condition (3.10). As a result, the new steady-state equilibrium establishes at higher wage and self-employment rate, and a level of wage-employment rate that is likely to be higher than before.

For this reason, in estimation of equation (3.16), only the variations in the change in wages and wage-employment structure can be used that are not correlated with changes in city level advantages in self-employment. Trade liberalization of the 1990s in Brazil provides such variations and a basis for devising an instrumental variable approach to address the concerns regarding endogeneity. The next section further discusses this issue.

3.5 Identification Strategy

As discussed above, the model indicates that the right-hand-side variables in (3.16) are likely to be endogenous and therefore contradict the conditions expressed in (3.22) and (3.23), which makes the OLS estimates of (3.16) inconsistent. Therefore, exogenous variation in the change in the average wage and employment rate should be explored to consistently identify $\alpha_1$ and $\alpha_2$.

An overview of the identification strategy is as follows. An instrumental variable estimation strategy is devised to address the concerns about endogeneity in (3.16). However, as will be discussed later, these instruments when directly applied to (3.16) weakly identify the coefficients. Therefore, equation (3.21) which is derived from the wage equation (3.18), is used to replace the average wage in equation (3.16) and then the instruments applied to the resulting reduced form, as the instruments are expected to perform well in this case. This strategy effectively deals with the weak identification. The results also indicate that this strategy effectively removes the endogeneity of the variables and provides consistent identification of the coefficients in (3.16). The reduced form equation is also of interest in itself as it essentially captures the causal effect of shift in local industrial composition on local self-employment rate.

To explain the IV strategy, it is useful to first explain the two different kinds of variation in the average wage. The change in the average wage can be decomposed as follows:
\[ \Delta W_c \equiv W_{ct} - W_{ct-1} = \sum_i \eta_{cit} w_{cit} - \sum_i \eta_{cit-1} w_{cit-1} \]
\[ = \sum_i (\eta_{cit} - \eta_{cit-1}) w_{cit-1} + \sum_i \eta_{cit} (w_{cit} - w_{cit}) \]
\[ = \sum_i \Delta \eta_{cit} w_{cit-1} + \sum_i \eta_{cit} \Delta w_{cit} \]
\[ = \Delta W_c^{(\Delta \eta)} + \Delta W_c^{(\Delta w)} \quad (3.24) \]

where \( \Delta W_c^{(\Delta \eta)} \) captures the change in the average wage that result from shifts in the industrial composition of local employment while \( \Delta W_c^{(\Delta w)} \) captures the change resulting from changes in local industrial wages. Therefore, condition (3.22) can be expressed as the following two sufficient conditions:

\[ \lim_{c \to \infty} \sum_c \Delta W_c^{(\Delta \eta)} \Delta \xi_c^{se} = \lim_{c \to \infty} \sum_c \sum_i \Delta \eta_{cit} w_{cit-1} \Delta \xi_c^{se} = 0 \quad (3.25) \]
\[ \lim_{c \to \infty} \Delta W_c^{(\Delta w)} \Delta \xi_c^{se} = \lim_{c \to \infty} \sum_c \sum_i \eta_{cit} \Delta w_{cit} \Delta \xi_c^{se} = 0 \quad (3.26) \]

A candidate set of instrumental variables that closely follow the structures of \( \Delta W_c^{(\Delta \eta)} \) and \( \Delta W_c^{(\Delta w)} \) but satisfy conditions (3.25) and (3.26) can be constructed by replacing \( w_{cit-1} \) and \( \Delta w_{cit} \) with \( \sigma_{it-1} = w_{it-1} - w_{1t-1} \) and \( \Delta \sigma_{it} = \Delta (w_{it} - w_{1t}) \) respectively and predicting \( \Delta \eta_{cit} \) and \( \eta_{cit} \) in a way that is orthogonal to \( \Delta \xi_c^{se} \). This can be seen from the following:

\[ \lim_{c \to \infty} \sum_c \sum_i \Delta \eta_{cit} \sigma_{it-1} \Delta \xi_c^{se} = \lim_{c \to \infty} \sum_i \sigma_{it-1} \sum_c \Delta \eta_{cit} \Delta \xi_c^{se} = 0 \quad (3.27) \]
\[ \lim_{c \to \infty} \sum_c \sum_i \hat{\eta}_{cit} \Delta \sigma_{it} \Delta \xi_c^{se} = \lim_{c \to \infty} \sum_i \Delta \sigma_{it} \sum_c \hat{\eta}_{cit} \Delta \xi_c^{se} = 0, \quad (3.28) \]
where $\Delta \hat{\eta}_{cit}$ and $\hat{\eta}_{cit}$ denote the predicted values of $\Delta \eta_{cit}$ and $\eta_{cit}$, respectively. In fact, such instruments closely follow the decomposition of the change in the measure of industrial composition:

$$\Delta R_c \equiv R_{ct} - R_{ct-1} = \sum_i \eta_{cit} \sigma_{it} - \sum_i \eta_{cit-1} \sigma_{it-1}$$

$$= \sum_i (\eta_{cit} - \eta_{cit-1}) \sigma_{it-1} + \sum_i \eta_{cit} (\sigma_{it} - \omega_{it})$$

$$= \sum_i \Delta \eta_{cit} \sigma_{it-1} + \sum_i \eta_{cit} \Delta \omega_{it}$$

$$= \Delta R_c^{(\Delta \eta)} + \Delta R_c^{(\Delta \omega)}, \quad (3.29)$$

where $\sigma_i = w_i - w_1$. The structures of $\Delta R_c^{(\Delta \eta)} = \sum_i \Delta \eta_{cit} \sigma_{it-1}$ and $\Delta R_c^{(\Delta \omega)} = \sum_i \eta_{cit} \Delta \omega_{it}$ is closely followed to construct the instruments. In particular, as explained in the next section, the distances of cities from major commercial ports of entry and exit in Brazil are used to predict how the trade liberalization of the 1990s impacted local structures of employment. Under the assumption that these measures of distance are not correlated with changes in local determinants of self-employment rate other than structures of employment and wages ($\Delta \xi_{ce}^{se}$), these instruments should satisfy conditions (3.27) and (3.28).

Such an instrumental approach directly applied to the baseline estimation equation (3.16) will be successful only if the instruments perform well in the associated 1st-stage regressions; i.e., they should be highly correlated with the endogenous variables. Comparing the decomposition of the change in the average wage in (3.24) with that of the change in the measure of industrial composition in (3.29), reveals a source of concern. It is expected that an instrument that follows the structure of $\Delta R_c^{(\Delta \eta)} = \sum_i \Delta \eta_{cit} \sigma_{it-1}$ and successfully predicts the change in local employment shares to be highly correlated with its counterpart $\Delta W_c^{(\Delta \eta)} = \sum_i \Delta \eta_{cit} \omega_{cit-1}$, as both of these changes are driven by changes in local employment shares. However, an instrument that follows the structure of $\Delta R_c^{(\Delta \omega)} = \sum_i \eta_{cit} \Delta \omega_{it}$, may not be strongly correlated with its counterpart $\Delta W_c^{(\Delta \omega)} = \sum_i \eta_{cit} \Delta \omega_{cit}$ no matter how well the local employment shares are being predicted, as the former is driven by changes in industry wage premia at the national level, while the latter is driven by changes in local industrial wages. This is essentially because averaging
wages across cities hide substantial, useful, variations among cities. Therefore the instrumental
approach that directly applies the instruments to the baseline equation may only be weakly
identifying the coefficients. This can be tested by the performance in the associated 1st-stage
regressions in a 2SLS procedure. It will be shown later that in fact this is the case here.

As a result, an alternative identification approach is followed. In particular, the wage equation
(3.18) is used to replace the average wage. Given that the instruments closely follow the
structure of the decomposition of the change in the measure of industrial composition, this
strategy is essentially useful since the resulting reduced form equation becomes a function of
only \( \Delta R_c \) and \( \Delta ER_c \). While the validity of instruments in this case relies on relatively stronger set
of assumptions, it effectively addresses the concerns regarding weak identification.

Equation (3.21) is used to replace \( \Delta W_{ct} \) in the baseline specification (3.16) to arrive at the
following reduce form equation:

\[
\Delta SR_{ct} = \Delta \alpha_3 t + \alpha_1 (1 + \beta) \Delta R_{ct} + \alpha_1 (\lambda + \alpha_2) \Delta ER_{ct} + \xi_{ct},
\]  

(3.30)

where \( \xi_{ct} = \alpha_1 \sum_i \eta_{jct} \varepsilon_{ict} + \Delta \varepsilon^{st}_{ct} \). Applying the same instrumental variables briefly discussed
above to equation (3.30), gives consistent estimates of the coefficients which can be used to back
out the parameters of the baseline specification, namely \( \alpha_1 \) and \( \alpha_2 \), provided the estimates of \( \gamma_2 \)
and \( \lambda \). Chapter 2 uses the same data and instruments used here and provides consistent estimates
of \( \gamma_2 \) and \( \lambda \) for this purpose.

3.6 The Instruments

This section explains the rationale behind the use of distance-based instruments and how they
are derived.

3.6.1 The Rationale

In a closed economy, distance from the outside world is not a relevant factor in determining
changes in the structure of employment and wages within cities. This is while, after trade
liberalization, the distance of a city from major commercial ports and the associated
transportation costs become an effective trade barrier between the local economy (city) and the
country’s major trade partners, given that lower tariffs are the same everywhere. Therefore, a
distance-based IV strategy should help capture the trade-induced variations across cities in the wage-employment rate and industrial composition.

In the long term, trade liberalization reallocates jobs across industries. As a result, some industries expand and some decline\(^83\), altogether differently in different regions. Drastic tariff reductions are mirrored in increased import penetration and unprecedented access to foreign markets, products, and technology. Trade liberalization is deemed to decrease demand for labour in industries where firms facing intensified foreign competition reduce labour costs to remain profitable (Goldberg & Pavcnik, 2003; Melitz, 2003), and increase demand for labour where it provides access to foreign markets. These impacts will manifest in the form of changes in the overall employment rate, industrial composition of the overall employment, and industry wages.

It is important to note that the trade-induced changes in industrial compositions and employment rates are not necessarily the same across different locations. As a result, the impact of trade liberalization on self-employment rate could be different in different locations, depending, among other things, on the extent and quality of exposure to foreign trade. According to Pavcnik, Blom, Goldberg, & Schady, (2002), the trade reforms in Brazil increased the average import penetration (the proportion of imports in total output plus net imports) from 5.7% in 1987 to 11.6% in 1998. They find the increase in import penetration in Brazil to be relatively small compared to a country such as Columbia that liberalized trade during the same period.\(^84\) They suggest that this has been the case potentially due to the large size of Brazil – i.e., there were regions where exposure was higher than others. In the context of Mexican and Brazilian cities, Chapters 1 and 2 above showed that the trade-induced shifts in the local compositions of employment substantially varied across cities of Mexico and Brazil.

It is hypothesized and later\(^85\) tested that the spatial pattern of exposure to foreign competition and the resulting changes in the local structures of employment can be partly explained by geographic distances of cities from major commercial border-crossings and ports of entry and exit, as the effective trade barrier after the reduction in tariffs that were similar for all localities.

\(^83\) The Heckscher-Ohlin model predicts labour reallocation from industries most exposed to the bigger tariff reductions to industries less exposed to trade. Pavcnik, Blom, Goldberg, and Schady (2002) find that sectors that experienced increases in import penetration contracted and that tariff declines led to contractions of employment in sectors with higher import penetration in Brazil.

\(^84\) Colombian manufacturing import penetration was about 21% in 1984 and significantly exceeded 30% after the reduction of tariffs in 1990 (Goldberg and Pavcnik, 2005).

\(^85\) Tested through the performance of the first-stage estimations in an instrumental variable estimation procedure.
Three factors are known to determine where a firm will locate: the cost of transportation (Fujita, 1988; Krugman, 1991), the location of other firms that are a source of spillovers (Henderson, 1974; Rauch, 1989), and the location of other firms that are a source of supply and demand (Rivera-Batiz, 1988; Krugman and Venables, 1995; Venables, 1996). Trade liberalization and the previously-non-existing access to foreign markets as well as foreign products breaks the importance of being close to larger domestic markets, as a result of which some firms may prefer to relocate to cities with less costly access to foreign trade. At the same time, firms facing more severe competition may decide to relocate away from areas that are greatly exposed to foreign trade. Distance should help explain the long term balance of these forces.

3.6.2 Constructing the Instruments

Trade liberalization of the 1990s in Brazil provides a basis for devising an instrumental variable approach to address the concerns regarding endogeneity of regressors in equation (3.16) and (3.30) and consistently estimate the parameters in these specifications. In particular, in the light of the New Economic Geography models and insights from gravity models of trade, the distances of each city from major commercial sea ports and border crossings with Argentina in Brazil are used to predict the variations in the pattern of change in the structure of employment and wages across cities. This strategy is essentially effective as self-employment is unlikely to be directly determined by an exogenous, time-invariant variable as such determined by nature (Glaeser, Rosenthal, Strange, 2010), while the extent of trade shock penetration is known to depend on factors such as being close to a good harbor (Disdier & Head, 2008). In particular, the identification assumption here is that variations in the residual change in self-employment rate across cities are unrelated to their pre-trade structure of employment and their distances from the major commercial ports of entry and exit n Brazil.

The instruments for the change in wage-worker industrial composition are constructed using as a guide its decomposition into share-based and wage-based parts:

\[ \Delta R_c = \Delta R_c^{(\Delta \eta)} + \Delta R_c^{(\Delta w)}, \]

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86 The exporters and firms who rely on imported inputs but do not face foreign competition.
where \( \Delta R_c^{(\Delta \eta)} = \sum_i \Delta \eta_{cit} \sigma_{it-1} \) indicates changes in industrial composition that are based on changes in local employment shares (\( \Delta \eta_{cit} \)) and \( \Delta R_c^{(\Delta w)} = \sum_i \eta_{cit} \Delta \sigma_{it} \) indicates changes that are based on changes in the national industry wage premia (\( \Delta \sigma_{it} \)). Each of these is used separately as a guide for constructing suitable instruments.

The share-based instrument, \( IV^{R(\Delta \eta)} \), and wage-based instrument, \( IV^{R(\Delta w)} \), are defined as:

\[
IV_c^{R(\Delta \eta)} = \sum_i \Delta \eta_{cit} \sigma_{it-1}, \tag{3.31}
\]

\[
IV_c^{R(\Delta w)} = \sum_i \hat{\eta}_{cit} \Delta \sigma_{it}, \tag{3.32}
\]

where \( \Delta \hat{\eta}_{cit} \) is the predicted change in employment share of industry \( i \) in city \( c \) based on the distances of this city-industry from major commercial border-crossings. Letting \( Dist_{cx} \) denote the distance of city \( c \) from the major commercial border crossing \( x \), and \( \ln(\cdot) \) be the natural logarithm function, the following equations describe the construction of the share-based instrument:

\[
\Delta \hat{\eta}_{ict} = \hat{\mu}_0 + \hat{\mu}_1 \eta_{ict-1} + \sum_x \hat{\mu}_2 i \ln(Dist_{cx}) \tag{3.33}
\]

\[
\hat{\eta}_{ict} = \eta_{ict-1} + \Delta \hat{\eta}_{ict}. \tag{3.34}
\]

The instruments for the change in wage-employment rate are constructed following similar steps. First, the trade-induced changes in employment rates are predicted:

\[
\Delta ER_{ic} = \hat{\phi}_0 + \hat{\phi}_1 ER_{ict-1} + \sum_x \hat{\phi}_2 i \ln(Dist_{cx}). \tag{3.35}
\]

Then the instruments are constructed as follows:
\[ IV_{ER}^{c} = \sum_{i} \Delta\Delta E_{R_{ic}}. \quad (3.36) \]

As shown in the appendix, the validity of \( IV_{c}^{R(\Delta \eta)} \) and \( IV_{c}^{ER} \) when directly applied to the baseline estimating equation relies on the following sufficient conditions:

\[ \underset{c \to \infty}{\text{plim}} \sum_{c} \Delta \zeta_{c}^{se} = 0 \quad (3.37) \]

\[ \underset{c \to \infty}{\text{plim}} \sum_{c} \ln(Dist_{cx}) \Delta \zeta_{c}^{se} = 0, \forall x. \quad (3.38) \]

The validity of \( IV_{c}^{R(\Delta \omega)} \) when directly applied to the baseline estimating equation, in addition to (3.37) and (3.38) above, relies on the following additional assumption:

\[ \underset{c \to \infty}{\text{plim}} \sum_{c} \eta_{ict-1} \Delta \zeta_{c}^{se} = 0 \quad (3.39) \]

These conditions are satisfied assuming that \( \Delta \zeta_{c}^{se} \) is not correlated with pre-trade compositions of employment across cities and their distances from the major commercial ports of entry and exit. When applied to the reduced form equation, independence of the measures of distance from \( \epsilon_{ic} \)'s are also required.

These assumptions do not seem implausible as the measures of distance are time-invariant attributes of the cities and the differencing the residuals in the baseline specification, \( \Delta \zeta_{c}^{se} \), has removed the time-invariant sources of variation in the error terms. Furthermore, these measures of distance are expected to affect the change in self-employment rate only through their effects on wage-employment rate and industrial compositions of employment, both of which are controlled for in the baseline specification. In other words, it is assumed that the distance from major commercial ports of entry and exit does not belong to the baseline specification as long as the change in the average wage and wage-employment rate are controlled included as regressors.
3.7 Data

The data used here are extracted from the tenth and eleventh Brazilian General Censuses for years 1991 and 2000, originally produced by the Brazilian Institute of Geography and Statistics (IBGE)\(^{87}\) and preserved and harmonized by Minnesota Population Center (2008). The sample is narrowed down to employed males and females aged 16 to 65, numbering to 2,710,578 and 3,470,536 individual observations, respectively for years 1991 and 2000.

Since the identification relies on variations across distinct local labour markets, it is necessary to define geographic limits that are consistent and comparable over time, are large enough so that residents do not commute beyond the boundaries to work, and are numerous. Ideal is to have a large number of time-consistent metropolitan areas in the sample. While Brazil is highly urbanized (80% of population and 90% of GDP), no official statistical or administrative entity is defined and included in the Brazilian census data reflects the concept of an economically independent city or urban agglomeration that is appropriate for economic analysis. The Brazilian census data is available for municipios, the main administrative level for local policy implementation and management, which are too small and too close to each other to be considered as independent economies and vary dramatically in size both between themselves and over time.\(^{88}\)

To properly define labour markets for the purpose of empirical analysis, this study adapts a grouping of municipios into 123 cities/metropolitan areas according to a comprehensive study done by the Government of Brazil on characterization and trends of urban network in Brazil (IPEA, IBGE, & UNICAMP, 2002). Figure (3.3) maps these distinct labour markets.

The detailed census industry definitions are also not comparable over time and hence impossible to match. This has forced the use of only fifteen, broadly defined industries here, namely Agriculture, fishing, and forestry; Mining; Manufacturing; Electricity, gas and water; Construction; Wholesale and retail trade; Hotels and restaurants; Transportation and communications; Financial services and insurance; Public administration and defense; Real estate and business services; Education; Health and social work; Private household services; and Other services. A higher number of industries would have been preferred but due to impossibility

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\(^{87}\) Instituto Brasileiro de Geografia e Estatística (or IBGE in short).

\(^{88}\) Population in Sao Paolo municipio about ten million while many other municipios with only a few thousand residents.
of matching the definition of industries across years in the census only the use of these 15 major categories was feasible. However, as shown in the appendix, this has no bearing on the consistency of OLS estimates or validity of instruments.

Using sampling weights, the data is properly aggregated from individual level into 123 cities over 15 broadly defined industries for the two years. This gives a panel with a maximum of 1,845 observations each year, for years 1991 and 2000. The square root of the number of sample observations used for calculating each observation in the panel is used as an analytical weight in the baseline and reduced-form equations.

3.8 Estimation Results

3.8.1 Overview

The OLS and IV estimation results associated with the baseline equation (3.16) indicate that the OLS estimates suffer from endogeneity and the IV estimates likely suffer from weak identification. The OLS estimation results of the reduced-from specification in (3.30) give point estimates of -0.66 and -0.10 for the coefficients of $\Delta R_c$ and $\Delta ER_c$, respectively. Based on the point estimates $\beta = 2.3$ and $\lambda = 0.90$ for the wage equation (3.18), the coefficient of $\Delta W_c$ and $\Delta ER_c$ in the baseline specification are approximated to be about -0.20 and -0.40, respectively. The IV estimates of the reduced-form specification indicate that the OLS results do not suffer from endogeneity. Moreover, the beta coefficients of the reduced-form specification indicate that local self-employment rate is much more responsive to changes in industrial composition of local employment, and therefore local wages, than changes in local employment rate. To the extent that the distance-based IV strategy is successful in capturing the impact of trade liberalization of the 1990s in Brazil on local structures of employments across Brazilian cities, the change in trade policy during this decade explains 74% of the variation across cities in the change in the industrial composition of local employments, 32% of the variations in the change in the wage-employment rate, and 21% of the variations in the change in the self-employment rate.

3.8.2 Results

Tables (3.2) reports the estimation results associated with the baseline specification in (3.16) and the reduced-form specification in (3.30). The OLS results associated with the baseline specification indicate negative and significant estimates for the coefficients of $\Delta W_c$ and $\Delta ER_c$. 

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While the coefficient of $\Delta ER_c$ is highly significant, the coefficient on $\Delta W_c$ is only significant at 10%. The IV results associated with this specification, which uses $IV_c^R(\Delta \eta)$, $IV_c^R(\Delta \omega)$, and $IV_c^{ER}$ as the instruments, shows substantial change in the estimates; the point estimates of the coefficient of $\Delta W_c$ becomes quite larger in magnitude but remains negative while that of $\Delta ER_c$ is no more significant and positive.

The change in the coefficient of $\Delta W_c$ is suggestive of endogeneity that is pushing its coefficient upward, consistent with what the theory had predicted. But it seems that change in the coefficient of $\Delta ER_c$ could be due to the weak performance of the instruments in the 1st-satge. The 1st-state F-Statistics associated with $\Delta W_c$ is low ($F = 7.29$) and a formal test of weak identification cannot reject weak identification. In order to address this issue and consistently estimate the causal effect of changes in city average wages and employment-rate on self-employment rate, the reduced-form estimation explained in section (3.5) is considered here.

Before discussing the estimation results associated with the reduced-form, it should be mentioned that these estimates are not directly comparable to those associated with the baseline specification. In order to compare the results, consistent estimates of the coefficients in the wage equation (3.18) are used to calculate the baseline coefficients from the estimates of the reduced-form specification. Following the approach described in Chapter 2, consistent estimates of the coefficients of the wage equation in (3.18) are estimated here to be 2.3 (with a robust and city-clustered standard error of 0.96) for $\beta$ and 0.9 (with a robust and city-clustered standard error of 0.84) for $\lambda$. These values are used to calculate the corresponding baseline coefficients from the reduced form specification. In what follows, these calculated baseline coefficients are quoted.

The OLS results associated with the reduced-form specification estimate $\alpha_1$, the coefficient of $\Delta W_c$ in the baseline specification, to be -0.20 and $\alpha_2$, the coefficient of $\Delta ER_c$ in the baseline specification, to be -0.40. These are lower in magnitude from the OLS estimates of the baseline model, pointing to a positive bias in OLS estimates of the baseline specification. As discussed before, from the theoretical model it was expected that to observe a clear upward bias for the average wage and a likely upward bias for the employment rate. The IV results associated with

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89 This is done by comparing the Kleibergen-Paap Wald rk test statistic, which is the robust alternative to Cragg-Donald Wald statistic when the error terms are not assumed to be i.i.d., Stock-Yogo weak ID test critical values, all provided in the output of ivreg2 command in STATA.

90 Given the 95% confidence intervals associated with $\beta$ in the wage equation (3.18) and the coefficient of $\Delta R_c$ in the reduced form specification (3.30), the estimated range for $\alpha_1$ is [-0.60, -0.09] and for $\alpha_2$ is [-2.54, 2.97].

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the reduced-form specification confirm that the OLS estimates of the reduced-form specification do not suffer from endogeneity.\textsuperscript{91}

The derived estimates of $\alpha_1 = -0.20$ and $\alpha_2 = -0.40$ suggest that one percent increase in the average wage reduces the self-employment rate by 0.20 percentage points and one percentage point increase in wage-employment rate reduces the self-employment rate by -0.40 percentage points, averaged across Brazilian cities. The average change in the average wage during 1991-2000 was 29\% while the average change in the wage-employment rate was about -0.029 percentage points, averaged across Brazilian cities. Given the estimates here, such a trend indicates a tension existing between the effects on the self-employment rate. Given the point estimates above, such a trend points to an average decline in the self-employment rate across cities. Average change in the self-employment rate across Brazilian cities during this period was about -0.015.

The reduced form specification is also interesting in its own right, in that it shows the effect of shifts in industrial composition. The results suggest that one standard deviation increase in the measure of industrial composition causes 0.53 standard deviations drop in the self-employment rate. This is while one standard deviation increase in the wage-employment rate causes 0.14 standard deviations decline in the self-employment rate. These results indicate that the self-employment rate is more responsive to changes in the industrial composition of employment, and therefore wages, than employment rate.

3.8.3 Robustness

It only remains to make sure of the robustness of the estimates. The literature on self-employment suggests a few other mechanisms that are shown to explain the differences in self-employment rate across space. The robustness of the findings in this study is tested here by including such alternative mechanisms in the reduced-form specification. Table (3.3) reports the

\textsuperscript{91} The test for equality of the OLS and IV estimates is formally carried out in this section by testing for exogeneity of the variable(s) of interest, separately or jointly, through comparing the distance of the OLS and IV estimates from each other via the endogtest(.) option of the ivreg2 command in STATA. The null hypothesis is that the specified endogenous regressor can actually be treated as exogenous, i.e., the IV estimates it is not significantly different from the OLS estimate for the variable(s) being tested. The P-value for the case of the estimates reported under the IV results associated with the reduced-form specification in table (3.3) is 0.64 for $\Delta R_c$, 0.41 for $\Delta ER_c$, and 0.70 jointly, indicating the null cannot be rejected for both variable.
results. Overall, the findings of this study remain robust to the inclusion of the alternative mechanisms.

Glaeser (2007) finds that age and education are important determinants of self-employment rate which explain fifty percent of its variation across cities. Changes in the cities’ average age and years of schooling are added to the right-hand-side of equation (3.30) to control for such effects (represented in table (3.4) by $\Delta sch_{clyr_c}$ and $\Delta age_c$, respectively). The previous conclusions remain robust to including these variables. While both measures appear as highly significant in the OLS, only the average city level change in years of schooling remains marginally significant with a negative sign after the application of the IV’s. The 1991 values of average city age and schooling are used as instruments for the added variables.

A vast literature has shown a relationship between agglomeration (versus competition) and innovation (Glaeser, Kallal, Scheinkman, and Shleifer, 1992; Agrawal, Kapur, & McHale, 2008; Simonen & McCann, 2008; Gerlach, Ronde, & Stahl, 2009; Agrawal, Cockburn, & Rosell, 2010; Glaeser, Kerr, & Ponzetto, 2009). A measure of industrial diversification in each city in 1991 is used to control for agglomeration vs. competition effects. Specifically, industrial diversification in each city is measured by one minus the Herfindahl Index\(^ {92}\), using the 1991 compositions of employment (represented in table (3.11) by $frac{1991}{c}$). Again, the previous estimates remain robust to including this measure and fractionalization does not seem to be a relevant factor in explaining the variation in self-employment across cities or city-industries in Brazil during the 1990s.

Most studies of self-employment focus on non-agriculture sectors. Here, three different cuts of the sample were also considered, the results of which are not reported since they were not different from the general results above. The first cut of the sample excluded observations belonging to the Agriculture, fishing, and forestry sector from the sample. Another cut, focused only on men. As a third cut, only those who were working fulltime were kept in the sample. The results were not different from those derived here using the full sample.

### 3.9 Conclusion

This paper addressed the question that how changes in local wages and employment rate cause changes in local self-employment rate. Building on the model in Beaudry, Green, and Sand

\(^{92}\) The sum of squared employment shares of industries within a city.
(2011), a multi-city, multi-industry search and bargaining model of a labour market was devised to understand how in a general equilibrium setting these variables relate to each other. This model provided the structure needed in a proper empirical investigation of the question above. The Brazilian census data for year 1991 and 2000 is then used to empirically identify the causal impacts of changes in local wages and employment rates across Brazilian cities. The difficulty in empirical identification of such impacts is in dealing with endogeneity that is present in a general equilibrium setting. The model provides a clean explanation of how the endogeneity works and the direction of the bias it causes.

Brazilian trade liberalization during the 1990s is used as a basis for identifying exogenous variations in local employment and wage structures than help identify their causal impacts on local self-employment rates. Variations across cities in terms of exposure to the effects of trade liberalization, captured by the distances of cities from major commercial ports of entry and exit in Brazil, were used to predict trade-induced changes in the local structures of employment and wages. Such a distance-based instrumental variable strategy effectively addresses the concerns about endogeneity.

It is found here that one standard deviation change in the average wage causes larger changes in the self-employment rate than one standard deviation change in the wage-employment rate. Moreover, given that the two variables do not necessarily move in the same direction in the long term, they can oppositely impact the self-employment rate. In fact, this is what happened in Brazil across cities during the 1990s; while in average the local average wages increased during this period, local employment rates declined, as a result of which self-employment rates also declined in average but by a small amount.

It is estimated here that during the 1990s, one percent increase in the average wage reduced the self-employment rate by 0.20 percentage points and one percentage point increase in wage-employment rate reduced the self-employment rate by 0.40 percentage points, average across Brazilian cities. The average change in the average wage during 1991-2000 was 29% while the average change in the wage-employment rate was about -0.029 percentage points, averaged across Brazilian cities.

Through impacts on wages, shifts in industrial composition of employment also substantially impact self-employment rate. The results suggest that one standard deviation increase in the measure of industrial composition causes 0.53 standard deviations drop in the self-employment
rate. This is while one standard deviation increase in the wage-employment rate causes 0.14 standard deviations decline in the self-employment rate. These results indicate that the self-employment rate is more responsive to changes in the industrial composition of employment, and therefore wages, than employment rate.

These estimates are shown to be statistically significant and robust to controlling for alternative mechanisms in the literature that are found to explain variations in self-employment rates across cities, such as changes in the average level of education and average age of city or its pre-trade diversification in industrial composition. To the extent that the distance-based IV strategy is successful in capturing the impact of trade liberalization of the 1990s in Brazil on local structures of employments across Brazilian cities, the change in trade policy during this decade explains 74% of the variation across cities in the change in the industrial composition of local employments, 32% of the variations in the change in the wage-employment rate, and 21% of the variations in the change in the self-employment rate.
<table>
<thead>
<tr>
<th>Export Destination</th>
<th>Change in Brazil’s Manufacturing Exports</th>
<th>Change in Brazil’s Manufacturing Imports</th>
</tr>
</thead>
<tbody>
<tr>
<td>Argentina</td>
<td>313%</td>
<td>Argentina</td>
</tr>
<tr>
<td>China</td>
<td>370%</td>
<td>China</td>
</tr>
<tr>
<td>France</td>
<td>36.3%</td>
<td>France</td>
</tr>
<tr>
<td>Germany</td>
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<td>Germany</td>
</tr>
<tr>
<td>Italy</td>
<td>30.1%</td>
<td>Italy</td>
</tr>
<tr>
<td>Japan</td>
<td>-5.84%</td>
<td>Japan</td>
</tr>
<tr>
<td>UK</td>
<td>34.1%</td>
<td>UK</td>
</tr>
<tr>
<td>US</td>
<td>102%</td>
<td>US</td>
</tr>
</tbody>
</table>

Table (3.2) – OLS and IV Estimation Results

<table>
<thead>
<tr>
<th>Dependent Variable:</th>
<th>Baseline Specification</th>
<th>Reduced-Form Specification</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\Delta SR_c$</td>
<td>OLS</td>
<td>IV</td>
</tr>
<tr>
<td>$\Delta W_c$</td>
<td>-0.03*</td>
<td>-0.17***</td>
</tr>
<tr>
<td></td>
<td>(0.02)</td>
<td>(0.06)</td>
</tr>
<tr>
<td>$\Delta ER_c$</td>
<td>-0.17***</td>
<td>-0.10**</td>
</tr>
<tr>
<td></td>
<td>(0.06)</td>
<td>(0.05)</td>
</tr>
<tr>
<td>$\Delta R_c$</td>
<td></td>
<td>-0.66***</td>
</tr>
<tr>
<td></td>
<td></td>
<td>(0.10)</td>
</tr>
<tr>
<td>$R^2$</td>
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<td>0.34</td>
</tr>
<tr>
<td>No. Obs.</td>
<td>1842</td>
<td>1842</td>
</tr>
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</table>

1st-Stage Statistics

<table>
<thead>
<tr>
<th></th>
<th>OLS</th>
<th>IV</th>
</tr>
</thead>
<tbody>
<tr>
<td>Partial $R^2$ of excluded instruments ($\Delta W_c$)</td>
<td>0.21</td>
<td></td>
</tr>
<tr>
<td>F-state ($\Delta W_c$)</td>
<td>7.29</td>
<td></td>
</tr>
<tr>
<td>P-value ($\Delta W_c$)</td>
<td></td>
<td>0.00</td>
</tr>
<tr>
<td>Partial $R^2$ of excluded instruments ($\Delta ER_c$)</td>
<td>0.41</td>
<td>0.41</td>
</tr>
<tr>
<td>F-state ($\Delta ER_c$)</td>
<td>25.2</td>
<td>25.2</td>
</tr>
<tr>
<td>P-value ($\Delta ER_c$)</td>
<td></td>
<td>0.00</td>
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<tr>
<td>Partial $R^2$ of excluded instruments ($\Delta R_c$)</td>
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<tr>
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<td>P-value ($\Delta R_c$)</td>
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<tr>
<td>Over-id (p-val.)</td>
<td>0.65</td>
<td>0.84</td>
</tr>
</tbody>
</table>

* *, **, ***: Significance at 10%, 5%, and 1%, respectively. (): City-clustered and robust standard errors. **Baseline Specification:** $\Delta SR_{ct} = \Delta \alpha_3t + \alpha_1 \Delta W_{ct} + \alpha_2 \Delta ER_{ct} + \Delta \rho_{ct}$. **Reduced-Form Specification:** $\Delta SR_{ct} = \Delta \alpha_3t + \alpha_1 (1 + \beta) \Delta R_{ct} + \alpha_4 (\lambda + \alpha_7) \Delta ER_{ct} + \rho_{ct}$. **IV:** The instruments used are $IV^R(\Delta \eta)$, $IV^R(\Delta \omega)$, and $IV^R_{ER}$. 128
Table (3.3) – Robustness Tests on the Reduced-Form Specification

<table>
<thead>
<tr>
<th>Dependent Variable: $\Delta S_{Rc}$</th>
<th>Reduced-Form Specification</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>OLS</td>
</tr>
<tr>
<td>$\Delta R_c$</td>
<td>-0.63***</td>
</tr>
<tr>
<td></td>
<td>(0.11)</td>
</tr>
<tr>
<td>$\Delta ER_c$</td>
<td>-0.11**</td>
</tr>
<tr>
<td></td>
<td>(0.05)</td>
</tr>
<tr>
<td>$\Delta schlyr_c$</td>
<td>-0.01**</td>
</tr>
<tr>
<td></td>
<td>(0.01)</td>
</tr>
<tr>
<td>$\Delta age_c$</td>
<td></td>
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<tr>
<td>$frac_{1991}$</td>
<td></td>
</tr>
</tbody>
</table>

Instrumented for the alternative mechanism

<table>
<thead>
<tr>
<th>$R^2$</th>
<th>Num. of Obs.</th>
</tr>
</thead>
<tbody>
<tr>
<td>0.36</td>
<td>1842</td>
</tr>
<tr>
<td>0.38</td>
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<tr>
<td>0.35</td>
<td>1842</td>
</tr>
<tr>
<td>0.35</td>
<td>1842</td>
</tr>
</tbody>
</table>

*, **, ***: Significance at 10%, 5%, and 1%, respectively. (): City-clustered and robust standard errors.

IV: The instruments used are $IV_c^{R(\Delta n)}$, $IV_c^{R(\Delta w)}$, and $IV_c^{ER_{w}}$ as well as the 1991-level of the average city years of schooling or age depending on specification.
Figure (3.1) – Brazil’s Major Trade Partners
Figure (3.2) – Map of Major Commercial Seaports in Brazil (indicates the 15 major seaports used as reference in this paper)


93 These major ports are: Port Santos (Santos - SP), Port Vitória (Vitória - ES), Port Paranaguá (Paranaguá - PR), Port Itaguai (Itaguai - RJ), Port Rio Grande (Rio Grande - RS), Port Rio de Janeiro (Rio de Janeiro - RJ), Port Itajaí (Itajaí - SC), Port Itaqui (São Luís - MA), Port São Sebastião (São Sebastião - SP), Port São Francisco do Sul (São Francisco do Sul - SC), Port Aratu (Candeias - BA), Port Manaus (Manaus - AM), Port Suape (Ipojuca - PE), Port Pecém (São Gonçalo do Amarante - CE), Port Ilhéus (Ilhéus - BA).
Figure (3.3) – Illustration of 123 distinct Labour Markets (Metropolitan Areas) in Brazil

Bibliography


Appendices

A.1 Theoretical Model in Chapters 1 & 2

Here, the theoretical model in Beaudry et al. (2011) is reproduced. The economy is characterized by $C$ local economies (cities) in which firms produce goods and individuals seek employment in $I$ sectors. To produce and make profits, firms create new jobs and seek to fill the costly vacancies and weight up the discounted costs of keeping those vacancies versus discounted expected profits they make by employing workers and paying a wage that is city-sector specific. In the same way as firms, individuals compare the discounted benefits from being unemployed with being an employee and receiving the city-sector wages. There is a random matching process through which workers are matched with firms and, as usual, in a steady-state equilibrium of this economy the value functions satisfy the standard Bellman relationship. All throughout the model it is assumed that workers are not mobile across cities, an assumption that if relaxed is not going to change the results.

There is a final good, denoted $Y$, which is an aggregation of output from a total of $I$ sectors:

$$Y = \left( \sum_{i=1}^{I} (a_i Z_i^X) \right)^{1/\chi}, \quad \chi < 1. \quad (A.1)$$

The price of the final good is normalized to 1, while the price of the good produced in sector $i$ is given by $p_i$. The total quantity of each sectoral good produced at the national level ($Z_i$) is the sum of local productions of that good.

In city $c$ sector $i$, filling a vacancy generates a flow of profits for a firm given by:

$$p_i - w_{ic} + \epsilon_{ic},$$

where $w_{ic}$ is city $c$ sector $i$’s specific wage, $\epsilon_{ic}$ is the city-sector specific cost advantage satisfying $\sum_c \epsilon_{ic} = 0$. Letting $V^f$ denote the discounted expected value of profits from a filled position and $V^v$ the discounted expected value of a vacancy, in steady state the value functions must satisfy the standard Bellman relationship:
\[ \rho V_{ic}^{f} = (p_i - w_{ic} + \epsilon_{ic}) + \delta(V_{ic}^{p} - V_{ic}^{f}), \quad (A.2) \]

where \( \rho \) is the discount rate and \( \delta \) is the exogenous death rate of matches. The discounted expected value of profits from a vacant position must satisfy:

\[ \rho V_{ic}^{p} = \phi_c(V_{ic}^{f} - V_{ic}^{p}), \quad (A.3) \]

where \( \phi_c \) is the probability a firm fills a posted vacancy. Here, for simplicity and with no loss of generality, the periodical cost to maintain the vacancy is assumed to be zero.

The discounted expected value of being employed in sector \( i \) in city \( c \), denoted \( U_{ic}^e \), must as well satisfy the Bellman equation:

\[ \rho U_{ic}^e = w_{ic} + \delta(U_{ic}^u - U_{ic}^e), \quad (A.4) \]

where \( U_{ic}^u \) represents the value associated with being unemployed when the worker’s previous job was in sector \( i \).

Representing the probability that an unemployed individual finds a job with \( \psi_c \) and the probability that an individual finding a job gets a random draw from jobs in all sectors (including sector \( i \)) – rather than being assigned a match in the previous sector – with \( 1 - \mu \), the value associated with being unemployed satisfies the Bellman relationship:

\[ \rho U_{ic}^u = b + \tau_c + \psi_c \left[ \mu U_{ic}^e + (1 - \mu) \sum_j (\eta_{jc} U_{jc}^e) - U_{ic}^u \right], \quad (A.5) \]

where \( b \) is the utility flow of an unemployment benefit, \( \tau_c \) is a city specific amenity term, and \( \eta_{jc} \) represents the fraction of city \( c \)’s vacant jobs that are in sector \( j \). The key assumption for being able to solve the model explicitly is that workers can only search while being unemployed.

Once a match is made, workers and firms bargain a wage. Assuming that there are always gains from trade between workers and firms for all jobs created in equilibrium, the bargaining is set according to the following rule:
\[
(V_{ic}^f - V_{ic}^v) = (U_{ic}^e - U_{ic}^u) \times \kappa, \quad (A.6)
\]

where \(\kappa\) indicates the relative bargaining power of workers and firms so that the higher it is, the lower is the bargaining power of the workers.

The probability a match is made is determined by the matching function:

\[
M((L_c - E_c), (N_c - E_c)),
\]

where \(L_c\) is the total number of workers in city \(c\), \(E_c\) is the number of employed workers (or matches) in city \(c\), and \(N_c = \sum_i N_{ic}\) is the number of jobs in city \(c\), with \(N_{ic}\) being the number of jobs in sector \(i\) in city \(c\). Given the exogenous death rate of matches, \(\delta\), and assuming a Cobb-Douglas form for the match function, the steady state condition is given by:

\[
\delta ER_c = M \left(1 - ER_c, \left(\frac{N_c}{L_c} - ER_c\right)\right) = (1 - ER_c)^\sigma \left(\frac{N_c}{L_c} - ER_c\right)^{1-\sigma}, \quad (A.7)
\]

where \(ER_c\) is the employment rate. It follows that the proportion of filled jobs and vacant jobs in sector \(i\) can be expressed as \(\eta_{ic} = \frac{N_{ic}}{\sum_i N_{ic}}\).

The number of jobs created in sector \(i\) in city \(c\), \(N_{ic}\), is determined by the free entry condition:

\[
c_{ic} = V_{ic}^v, \quad (A.8)
\]

where \(c_{ic}\) is the cost of creating a marginal job and is necessarily increasing in the number of new jobs being created locally in that sector to have cities with employment across a wide range of sectors. Cities could also have a comparative advantage in creating certain types of jobs relative to others. Therefore, it is assumed that \(c_{ic}\) is a decreasing function of the city-sector specific measure of advantage denoted \(\Omega_{ic}\):

\[
c_{ic} = \frac{N_{ic}}{Y_i + \Omega_{ic}}.
\]
where \( Y_i \) reflects any systematic differences in cost of entry across sectors, which allows to assume that \( \sum c \Omega_{ic} = 0 \).

Finally, the probability an unemployed worker finds a match and the probability a firm fills a vacancy respectively satisfy:

\[
\psi_c = \frac{\delta ER_c}{1 - ER_c} \quad \text{and} \quad \phi_c = \left( \frac{1 - ER_c}{\delta ER_c} \right)^{\frac{\sigma}{\sigma - 1}}. \quad (A.9)
\]

A steady state equilibrium in which the price of sectoral output is taken as given, consists of value of \( N_{ic}, w_{ic}, \) and \( ER_c \) that satisfy equations (A.6), (A.7), and (A.8). These equilibrium values will depend on (among other things) the city specific productivity parameters \( \Omega_{ic} \) and \( \epsilon_{ic} \).

An equilibrium for the entire economy has the additional requirement that the prices for sectoral goods must ensure that markets for these goods clear.

Solving the model for city-sector wages gives the following relationship:

\[
w_{ic} = \gamma_{c0} + \gamma_{c1}p_i + \gamma_{c2} \sum_j \eta_{jc} w_{jc} + \gamma_{c1} \epsilon_{ic}, \quad (A.10)
\]

where the coefficients are:

\[
\gamma_{c0} = \frac{b + \tau_c}{\psi_c(1 - \mu) + \rho(\rho + \psi_c + \delta) + \delta \psi_c(1 - \mu)} + \frac{(\rho + \psi_c + \delta)}{\rho(\rho + \psi_c + \delta) + \delta \psi_c(1 - \mu) + \delta \psi_c(1 - \mu) + \delta \psi_c(1 - \mu)}
\]

\[
\gamma_{c1} = \frac{1}{\frac{\rho(\rho + \psi_c + \delta) + \delta \psi_c(1 - \mu)}{\rho(\rho + \psi_c + \delta) + \delta \psi_c(1 - \mu) + \delta \psi_c(1 - \mu)}}
\]

\[
\gamma_{c2} = \frac{1}{\left[ 1 + \frac{\rho}{\psi_c(1 - \mu)} + \frac{\rho(\rho + \psi_c + \delta) + \delta \psi_c(1 - \mu)}{(\rho + \psi_c + \delta) \psi_c(1 - \mu)} \right] \cdot \left[ 1 + \frac{\delta}{\rho + \psi_c} \right]}
\]
These coefficients are implicitly functions of the employment rate through $\psi_c$ and $\phi_c$.

To make progress toward an estimating relationship and overcome the simultaneity inherent in this equation, equation (A.10) can be manipulated and transformed to:

$$w_{ic} = \tilde{d}_{ic} + \frac{\gamma_1}{\gamma_1} \frac{\gamma_{c1}}{(1 - \gamma_{c2})} \sum_j \eta_{c1} (w_j - w_1) + \gamma_{c2} \frac{\gamma_{c2}}{(1 - \gamma_{c2})} \sum_j \eta_{c2} \epsilon_{jc} + \gamma_{c1} \epsilon_{ic}, \quad (A.11)$$

where $w_i - w_1$ is the national level wage premium in sector $i$ relative to sector 1, $\gamma_1$ is the average of $\gamma_{c1}$ across cities, $\tilde{d}_{ic} = d_{ic} - \frac{\gamma_{c1}}{\gamma_1} \frac{\gamma_{c2}}{(1 - \gamma_{c2})} \sum_j \eta_{c1} \tilde{d}_j$ with $d_{ic} = \gamma_{c0} [1 + \frac{\gamma_{c2}}{(1 - \gamma_{c2})}] + \gamma_{c1} p_i + \gamma_{c1} \left[ \frac{\gamma_{c2}}{(1 - \gamma_{c2})} \right] p_1$, $p_i$ being the price of good $i$ that is the product of sector $i$, and $\tilde{d}_j = \frac{1}{C} \sum_{c=1}^{c} \eta_{c1} (\epsilon_{jc} - \epsilon_{1c})$ being a sector specific constant.

So far, the employment rate in a city is hidden in the $\gamma$ parameters and the sectoral shares were taken as given. To capture the dependence of wages on the city’s employment rate more explicitly, Beaudry et al. (2009) take a linear approximation of (A.11) around the point where cities have identical sectoral composition ($\eta_{ic} = \eta_l = \frac{1}{l}$) and employment rates ($ER_c = ER$), which arises when $\epsilon_{ic} = 0$ and $\Omega_{ic} = 0$. Furthermore, to eliminate the city level fixed effects driven by the amenity term, $\tau_c$, they focus on the differences in wages within a city-sector cell across two steady state equilibria, denoted $\Delta w_{ci}$:

$$\Delta w_{ic} = \Delta d_i + \frac{\gamma_2}{(1 - \gamma_2)} \Delta \sum_j \eta_{c1} (w_j - w_1) + \gamma_{l5} \Delta ER_c + \Delta \xi_{ic}, \quad (A.12)$$

where $\Delta d_i$ is a sector specific effect ($\Delta d_i = \gamma_1 \frac{\gamma_2}{(1 - \gamma_2)} \Delta p_1 + \gamma_1 \Delta p_i$) that can be captured in an empirical specification by including sector dummies, and $\Delta \xi_{ic} = \gamma_1 \Delta \epsilon_{ic} + \gamma_1 \frac{\gamma_2}{(1 - \gamma_2)} \sum_j \frac{1}{I} \Delta \epsilon_{jc}$ is the error term, with $I$ being the total number of sectors.

In this study interest is in estimating the coefficient on the changes in average measure of industrial composition in (A.12); $\frac{\gamma_2}{(1 - \gamma_2)}$. Consistent estimates of this coefficient would provide an estimate of the extent of city-level strategic complementarity between wages in different sectors by backing out $\gamma_2$. The coefficient $\frac{\gamma_2}{(1 - \gamma_2)}$ is of interest in its own right as it provides an estimate
of the total – direct and feedback – effect of a one unit increase in average city wages on within sector wages, as opposed to $\gamma_2$, which provides the partial unidirectional effect.

Examining wages in the same sector in different cities, a positive value for $\frac{\gamma_2}{(1-\gamma_2)}$ implies that for example agriculture wages will be higher in cities where employment is more heavily weighted toward high rent sectors, where high rent sectors are defined in term of national level wage premia. This arises in the model because the workers in that sector have better outside option to use when bargaining with firms in cities with higher rents (cities with a distribution of employment more in favour of higher paying sectors).

The conventional accounting measure of the impact of a compositional change in the context of the model above is captured by $A_c = \sum_j (\eta_{jct+1} - \eta_{jct}) (w_{jt} - w_{1t}) = \sum_j (\eta_{jct+1} - \eta_{jct}) v_{jt}$; the change in average wages due to the compositional change while keeping the wages constant. In the absence of wage complimentarity among sectors in a city, the accounting measure will be the total impact of this compositional change. However, at the presence of the general equilibrium mechanism through which the city-sector wages in a city become complementarily related according to equation (A.12) or (A.10), the dynamics of the model imply that the total impact of such a compositional change is equal to $A_c + \frac{\gamma_2}{1-\gamma_2} \Delta R_c$. The change in the measure of industrial composition can be decomposed as:

$$\Delta R_{ct} = \sum_i (\eta_{cit+1} - \eta_{cit}) v_{it} + \sum_i \eta_{cit+1} (v_{it+1} - v_{it}) = A_c + \sum_i \eta_{cit+1} (v_{it+1} - v_{it}).$$

Thus, the total impact becomes $A_c + \frac{\gamma_2}{1-\gamma_2} \Delta R_c = \left(1 + \frac{\gamma_2}{1-\gamma_2}\right) A_c + \frac{\gamma_2}{1-\gamma_2} \sum_i \eta_{cit+1} (v_{it+1} - v_{it})$ where $\frac{\gamma_2}{1-\gamma_2}$ now clearly indicates the magnitudes of order the general equilibrium impact is larger than the conventional accounting measure in the absence of any changes in wage premia impacted form the compositional change. If $\frac{\gamma_2}{(1-\gamma_2)}$ is estimated to be zero then the accounting measure completely captures the effects of the composition shift.
A.2 Deriving the Identification Conditions in Chapters 1 & 2

As described in the text, interest is in the condition:\(^94\)

\[
\lim_{C,I \to \infty} \frac{1}{I} \sum_{i=1}^{I} \sum_{c=1}^{C} \Delta R_c \Delta \xi_{ic} = 0, \quad (A.13)
\]

which, using \(R = \sum_j \eta_{jc}(w_j - w_1)\), can be written as:

\[
\lim_{C,I \to \infty} \frac{1}{I} \sum_{i=1}^{I} \sum_{c=1}^{C} \left[ \sum_{j=1}^{1} \Delta \eta_{jc}(w_j - w_1) + \sum_{j=1}^{I} \eta_{jc}(w_j - w_1) \right] \Delta \xi_{ic}
\]

or:

\[
\lim_{C,I \to \infty} \frac{1}{I} \left[ \sum_{j=1}^{I} (w_j - w_1) \sum_{c=1}^{C} \Delta \eta_{jc} \sum_{i=1}^{1} \Delta \xi_{ic} + \sum_{j=1}^{I} \Delta (w_j - w_1) \sum_{c=1}^{C} \eta_{jc} \sum_{i=1}^{1} \Delta \xi_{ic} \right]. \quad (A.14)
\]

Handling the limiting arguments sequentially\(^95\) and allowing for \(C \to \infty\) first, we can analyze the two parts of (A.14) separately. The first is:

\[
\lim_{C \to \infty} \frac{1}{C} \sum_{c=1}^{C} \Delta \eta_{jc} \sum_{i=1}^{1} \Delta \xi_{ic}. \quad (A.15)
\]

Given the decomposition of \(\epsilon_{ic} = \hat{\epsilon}_c + \nu_{ic}^\epsilon\), where \(\sum_i \nu_{ic}^\epsilon = 0\), using the following first linear approximation of the equilibrium equation for city-sector shares:

\[
\eta_{ic} \approx \frac{1}{I} + \pi_1 \left( \epsilon_{ic} - \frac{1}{I} \sum_j \epsilon_{jc} \right) + \pi_2 \left( p_i \Omega_{ic} - \frac{1}{I} \sum_j p_j \Omega_{jc} \right), \quad (A.16)
\]

\(^94\) Throughout this section of the appendix the \(t\) subscript is omitted for simplicity.\(^95\) Following the approach discussed in Beaudry et al. (2011).
\[ \Delta \eta_{jc} = \pi_1 \left( \Delta \epsilon_{jc} - \frac{1}{I} \Delta \sum_j \epsilon_{jc} \right) + \pi_2 \left( \Delta p_j \Omega_{jc} - \frac{1}{I} \Delta \sum_j p_j \Omega_{jc} \right) \]
\[ = \pi_1 \left[ \Delta (\hat{\epsilon}_c + v_{cj}) - \frac{1}{I} \Delta \sum_j (\hat{\epsilon}_c + v_{cj}) \right] + \pi_2 \left( \Delta p_j \Omega_{jc} - \frac{1}{I} \Delta \sum_j p_j \Omega_{jc} \right) \]
\[ = \pi_1 (\Delta \hat{\epsilon}_c + \Delta v_{cj}^e - \Delta \hat{\epsilon}_c) + \pi_2 \left( \Delta p_j \Omega_{jc} - \frac{1}{I} \Delta \sum_j p_j \Omega_{jc} \right) \]
\[ = \pi_1 \Delta v_{cj}^e + \pi_2 (\Delta p_j \Omega_{jc} - \Delta \hat{\Omega}_c). \quad (A.17) \]

Also, since \( \Delta \xi_{ic} = \gamma_1 \Delta \hat{\epsilon}_{ic} + \gamma_1 \frac{\gamma_2}{1 - \gamma_2} \sum_j \frac{1}{I} \Delta \epsilon_{jc} \):

\[ \sum_i \Delta \xi_{ic} = \sum_i \left( \gamma_1 \Delta (\hat{\epsilon}_c + v_{ci}) + \gamma_1 \frac{\gamma_2}{1 - \gamma_2} \frac{1}{I} \sum_j \Delta (\hat{\epsilon}_c + v_{cj}) \right) \]
\[ = \sum_i \left( \gamma_1 \Delta (\hat{\epsilon}_c + v_{ci}) + \gamma_1 \frac{\gamma_2}{1 - \gamma_2} \Delta \hat{\epsilon}_c \right) \]
\[ = I \gamma_1 \Delta \hat{\epsilon}_c + I \gamma_1 \frac{\gamma_2}{1 - \gamma_2} \Delta \hat{\epsilon}_c \]
\[ = I \left( \gamma_1 + \gamma_1 \frac{\gamma_2}{1 - \gamma_2} \right) \Delta \hat{\epsilon}_c. \quad (A.18) \]

Then, given that \( E(\Delta \hat{\epsilon}_c) = 0 \) (again, recalling that economy-wide trends are removed) and if \( \Delta \hat{\epsilon}_c \) is independent of \( \Delta v_{ic}^e \) and \( \Delta \sum_j \sum_{c=1}^c \eta_{jc} \sum_{i=1}^1 \Delta \xi_{ic} \), it is straight forward to show that (A.15) equals zero.

The second component is:

\[ p \lim_{C \to \infty} \frac{1}{C} \sum_{c=1}^C \sum_{i=1}^1 \Delta \xi_{ic}, \quad (A.19) \]

where \( \sum_{i=1}^1 \Delta \xi_{ic} \) is again given by (A.18), while \( \eta_{jc} \) is given by equation (A.16) in the text. For (A.19) to be zero it is required in addition that \( \Delta \hat{\epsilon}_c \) be independent of past values of \( v_{ic}^e \) and of
Thus, if $\Delta \hat{\epsilon}_c$ is independent of the past and is independent of $\Delta u_{ic}$ and of $\Delta \Omega_{jc} - \Delta \Omega_{jc}$, then (A.13) equals zero and OLS is consistent.

Interest is also in the conditions under which our instruments can provide consistent estimates. Apart from the instruments being correlated with $\Delta R_c$, the condition required for a given instrument, $Z_c$, is:

$$\text{plim}_{c,i \to \infty} \sum_c \sum_l Z_c \Delta \xi_{ic} = \text{plim}_{c,i \to \infty} \sum_c Z_c \sum_l \Delta \xi_{ic} = 0$$

Given (A.18):

$$\text{plim}_{c,i \to \infty} \sum_c Z_c \sum_l \Delta \xi_{ic} = 0 \Rightarrow \text{plim}_{c \to \infty} \sum_c Z_c \Delta \hat{\epsilon}_c = 0$$

(A.20)

For IV $\Delta \eta$:

$$IV \Delta \eta = \sum_j \left( \hat{\eta}_{cjt} - \eta_{cjt-1} \right) \omega_{jt-1},$$

where

$$\Delta \hat{\eta}_{cjt} = \hat{\psi}_0 + \hat{\psi}_1 \eta_{cjt-1} + \sum_x \hat{\psi}_2 j ln(dist_{cx}).$$

Therefore:

$$\text{plim}_{c \to \infty} \sum_c Z_c \Delta \hat{\epsilon}_c = \text{plim}_{c \to \infty} \sum_c \sum_j \left( \hat{\eta}_{cjt} - \eta_{cjt-1} \right) \omega_{jt-1} \Delta \hat{\epsilon}_c = 0$$

$$\Rightarrow \text{plim}_{c \to \infty} \sum_j \omega_{jt-1} \sum_c \hat{\eta}_{cjt} \Delta \hat{\epsilon}_c - \sum_j \omega_{jt-1} \sum_c \eta_{cjt-1} \Delta \hat{\epsilon}_c = 0$$

$$\Rightarrow \text{plim}_{c \to \infty} \sum_j \omega_{jt-1} \sum_c \left( \hat{\psi}_0 + \hat{\psi}_1 \eta_{cjt-1} + \sum_x \hat{\psi}_2 j ln(dist_{cx}) \right) \Delta \hat{\epsilon}_c$$

$$- \text{plim}_{c \to \infty} \sum_j \omega_{jt-1} \sum_c \eta_{cjt-1} \Delta \hat{\epsilon}_c = 0$$
\[ \lim_{c \to \infty} \hat{\psi}_0 \sum_j \omega_{jt-1} \sum_c \Delta \hat{\epsilon}_c + \lim_{c \to \infty} \sum_j \omega_{jt-1} \hat{\psi}_1 \sum_c \eta_{cjt-1} \Delta \hat{\epsilon}_c \]
\[ + \lim_{c \to \infty} \sum_j \omega_{jt-1} \hat{\psi}_2 \sum_x \sum_c \ln(\text{dist}_{cx}) \Delta \hat{\epsilon}_c \]
\[ - \lim_{c \to \infty} \sum_j \omega_{jt-1} \sum_c \eta_{cjt-1} \Delta \hat{\epsilon}_c = 0 \quad (A.21) \]

It can be seen that for (A.21) to be satisfied it is sufficient that:

\[ \lim_{c \to \infty} \sum_c \Delta \hat{\epsilon}_c = 0 \]
\[ \lim_{c \to \infty} \sum_c \eta_{cjt-1} \Delta \hat{\epsilon}_c = 0 \]
\[ \lim_{c \to \infty} \sum_c \ln(\text{dist}_{cx}) \Delta \hat{\epsilon}_c = 0 \quad \forall x \]

Similar conditions for the other instruments can be derived.

### A.3 Data in Chapter 1

The Mexican Household Census data for years 1990 and 2000 were extracted from IPUMS-International website accessible to public at [https://international.ipums.org/international/](https://international.ipums.org/international/). Among various sorts of individual level information the dataset includes information on age and gender, marital status, nativity, ethnicity and language, education, work, income, and migration. The information on work specifies numerous variables such as employment status, occupation, industry and hours of work. The main variable used as the indicator of income is ‘earned income’ (variable INCEARN from the income category), which reports total income from labour (from wage, a business, or a farm) in previous month. Using this information jointly with information on class of worker (CLASSWK from the work category) the wage/salary earners can be distinguished from the pool of labour who earns income by running a business or a farm. This group, the wage/salary earners, form the sample used in this study. Wage or salary earners whose industries of work or income or demographic attributes are not identified are dropped from the sample.
The income variable (INCEARN) is reported in nominal Pesos, the currency of Mexico, and is top-coded. In order to carry out the inferences using the data for the two years, the 1990 values of income are converted to constant-year-2000 figures using the 1990 consumer price index (CPI) taken from International Financial Statistics (IFS). Following Aydemir & Borjas (2007, p.706), who have worked with the same database, to deal with the top-coded monthly incomes the multiplier of 1.5 is applied. In addition, in 1993 the ‘New Peso’ was coined that is equivalent to a thousand ‘Old Pesos’. The 1990 values of monthly income are adjusted for this deletion of three zeros from the Peso bills after 1993.

Using the data on years of schooling and age, a measure of experience at work is constructed according to “Experience = Age – 6 – Years of Schooling,” where ‘6’ is the mandatory age for schooling in Mexico. The migration information contained in the database makes it possible to distinguish between foreign and domestic immigration. In addition, the information on whether an individual speaks an indigenous language allows for controlling for being part of an indigenous minority. All these variables are used in filtering out the impact of workers’ attributes on the income they received in order to extract the wages intrinsically paid by sectors.

In 2004, a joint effort between CONAPO (Consejo Nacional de Población), INEGI (Instituto Nacional de Estadística, Geografía, e Informática) and the Ministry of Social Development (Secretaría de Desarrollo Social or SEDESOL) defines the metropolitan areas as:96

- A group of two or more municipalities in which a city with a population of at least 50,000 is located, whose urban area extends over the limit of the municipality that originally contained the core city incorporating either physically or under its area of direct influence other adjacent predominantly urban municipalities all of which have a high degree of social and economic integration or are relevant for urban politics and administration; or

- a single municipality in which a city with population of at least one million is located and fully contained (that is, it does not transcend the limits of a single municipality); or

- a city with a population of at least 250,000 which forms a metropolitan area with other cities in the United States.

It should be noted that north-western and south-eastern states are divided into a small number of large municipalities whereas central states are divided into a large number of smaller municipalities. As such, metropolitan areas in the northwest usually do not extend over more

than one municipality whereas metropolitan areas in the centre extend over many municipalities. Few metropolitan areas extend beyond the limits of one state, namely: Greater Mexico City (Federal District, Mexico and Hidalgo), Puebla-Tlaxcala (Puebla and Tlaxcala, but excludes the city of Tlaxcala), Comarca Lagunera (Coahuila and Durango), and Tampico (Tamaulipas and Veracruz). The map of the metropolitan areas is presented at the end of this section, which can be compared with the population density map of Mexico in year 2000.

A.4 Data in Chapters 2 & 3

The Brazilian Household Census data for years 1991 and 2000 were extracted from IPUMS-International website accessible to public at https://international.ipums.org/international/. Among various sorts of individual level information the dataset includes information on age and gender, marital status, nativity, ethnicity and language, education, work, income, and migration. The information on work specifies numerous variables such as employment status, occupation, industry and hours of work. The main variable used as the indicator of income is ‘earned income’ (variable INCEARN from the income category), which reports total income from labour (from wage, a business, or a farm) in previous month. Using this information jointly with information on class of worker (CLASSWK from the work category) the wage/salary earners can be distinguished from the pool of labour who earns income by running a business or a farm.

Brazilian currency changed considerably over time. In March 1990, the cruzeiro replaced the cruzado, with no change in value. In 1993, the cruzeiro reais replaced the cruzeiro, with 1 cruzeiro reais = 1000 cruzeiros. Finally, in 1994 the currency was changed to the real, where 1 real = 2750 cruzeiros reais. The income data were made comparable across years taking into account the above changes and using the Brazilian CPI for year 1991 from the World Bank’s WDI online database to express wages in constant-year-2000 denomination.

Using the data on years of schooling and age, a measure of experience at work is constructed according to “Experience = Age – 6 – Years of Schooling,” where ‘6’ is the mandatory age for schooling in Mexico. The migration information contained in the database makes it possible to distinguish between foreign and domestic immigration. In addition, the information on whether an individual speaks an indigenous language allows for controlling for being part of an indigenous minority. All these variables are used in filtering out the impact of workers’ attributes on the income they received in order to extract the wages intrinsically paid by sectors.
Since the identification relies on variations across distinct local labour markets, it is necessary to define geographic limits that are consistent and comparable over time, are large enough so that residents do not commute beyond the boundaries to work, and are numerous. Ideal is to have a large number of time-consistent metropolitan areas in the sample. While Brazil is highly urbanized (80% of population and 90% of GDP), no official statistical or administrative entity is defined and included in the Brazilian census data reflects the concept of an economically independent city or urban agglomeration that is appropriate for economic analysis. The Brazilian census data is available for municipios, the main administrative level for local policy implementation and management, which are too small and too close to each other to be considered as independent economies and vary dramatically in size both between themselves and over time.  

To properly define labour markets for the purpose of empirical analysis, this study adapts a grouping of municipios into 123 cities/metropolitan areas according to a comprehensive study done by the Government of Brazil on characterization and trends of urban network in Brazil (IPEA, IBGE, & UNICAMP, 2002).

A.5 Validity of Instruments in Chapter 3

The validity of the instruments when directly applied to the baseline estimating equation relies on the following sufficient conditions. For $IV^{R(\Delta \eta)}_c$:

\[
\begin{align*}
\lim_{c \to \infty} \sum_c IV^{R(\Delta \eta)}_c \Delta \zeta^s_e &= 0 \quad (A.22) \\
\Rightarrow \lim_{c \to \infty} \sum_c \sum_i \Delta \bar{\eta}_{cit} \sigma_{it-1} \Delta \zeta^s_e &= 0 \\
\Rightarrow \lim_{c \to \infty} \sum_i \sigma_{it-1} \sum_c \Delta \bar{\eta}_{cit} \Delta \zeta^s_e &= 0 \\
\Rightarrow \lim_{c \to \infty} \sum_i \sigma_{it-1} \sum_c \left( \hat{\mu}_0 + \hat{\mu}_1 \eta_{it-1} + \sum_x \hat{\mu}_2 l(Dist_{cx}) \right) \Delta \zeta^s_e &= 0
\end{align*}
\]

\[97\text{ Population in Sao Paolo municipio about ten million while many other municipios with only a few thousand residents.}\]
\[
\Rightarrow \lim_{c \rightarrow \infty} \sum_{i} \omega_{it-1} \bar{\mu}_0 \sum_{c} \Delta \zeta^{se}_c + \lim_{c \rightarrow \infty} \sum_{i} \omega_{it-1} \bar{\mu}_1 \sum_{c} \eta_{ict-1} \Delta \zeta^{se}_c \\
+ \lim_{c \rightarrow \infty} \sum_{i} \omega_{it-1} \hat{\mu}_2 \sum_{x} \sum_{c} \ln(Dist_{cx}) \Delta \zeta^{se}_c = 0 \quad (A.23)
\]

For \(IV^R_{c} \Delta w\):

\[
\Rightarrow \lim_{c \rightarrow \infty} \sum_{c} IV^R_{c} \Delta \zeta^{se}_c = 0 \quad (A.24)
\]

\[
\Rightarrow \lim_{c \rightarrow \infty} \sum_{i} \sum_{c} \hat{\eta}_{ict} \Delta \sigma_{it} \Delta \zeta^{se}_c = 0
\]

\[
\Rightarrow \lim_{c \rightarrow \infty} \sum_{i} \Delta \sigma_{it} \sum_{c} \hat{\eta}_{ict} \Delta \zeta^{se}_c = 0
\]

\[
\Rightarrow \lim_{c \rightarrow \infty} \sum_{i} \Delta \sigma_{it} \sum_{c} (\eta_{ict-1} + \hat{\Delta} \eta_{ict}) \Delta \zeta^{se}_c = 0
\]

\[
\Rightarrow \lim_{c \rightarrow \infty} \sum_{i} \Delta \sigma_{it} \sum_{c} \eta_{ict-1} \Delta \zeta^{se}_c + \lim_{c \rightarrow \infty} \sum_{i} \Delta \sigma_{it} \sum_{c} \hat{\Delta} \eta_{ict} \Delta \zeta^{se}_c = 0, \quad (A.25)
\]

which is essentially the same as (A.23).

And for \(IV^R_{c} ER\):

\[
\lim_{c \rightarrow \infty} \sum_{c} IV^R_{c} \Delta \zeta^{se}_c = 0 \quad (A.26)
\]

\[
\Rightarrow \lim_{c \rightarrow \infty} \sum_{c} \sum_{i} \Delta \overline{ER}_{ic} \Delta \zeta^{se}_c = 0
\]

\[
\Rightarrow \lim_{c \rightarrow \infty} \sum_{i} \sum_{c} \left( \hat{\phi}_0 + \hat{\phi}_1 \overline{ER}_{ict-1} + \sum_{x} \hat{\phi}_2i \ln(Dist_{cx}) \right) \Delta \zeta^{se}_c = 0
\]

\[
\Rightarrow \lim_{c \rightarrow \infty} \hat{\phi}_0 \sum_{c} \Delta \zeta^{se}_c + \lim_{c \rightarrow \infty} \sum_{i} \hat{\phi}_1 \sum_{c} \overline{ER}_{ict-1} \Delta \zeta^{se}_c \\
+ \lim_{c \rightarrow \infty} \sum_{i} \hat{\phi}_2i \sum_{x} \sum_{c} \ln(Dist_{cx}) \Delta \zeta^{se}_c = 0 \quad (A.27)
\]
Sufficient conditions for (A.23), (A.25) and (A.27) to be satisfied are:

\[ \lim_{c \to \infty} \varphi_0 \sum_c \Delta \zeta^{se}_c = 0 \quad (A.28) \]

\[ \lim_{c \to \infty} \sum_c \ln(\text{Dist}_{cx}) \Delta \zeta^{se}_c = 0 \quad \forall x \quad (A.29) \]

\[ \lim_{c \to \infty} \sum_c \eta_{ict-1} \Delta \zeta^{se}_c = 0. \quad (A.30) \]

\[ \lim_{c \to \infty} \sum_c E_R_{ict-1} \Delta \zeta^{se}_c = 0. \quad (A.31) \]

When applied to the reduced-form specification (3.30), in addition to conditions above, the following conditions should be satisfied. Here, only the condition for \( IV_c^{R(\Delta \eta)} \) is presented. Similar conditions for other instruments can be derived:

\[ \lim_{c \to \infty} \sum_c IV_c^{R(\Delta \eta)} \left( \Delta \sum_l \eta_{jct} \epsilon_{ict} + \Delta \zeta^{se}_{ct} \right) = 0 \quad (A.32) \]

\[ \Rightarrow \lim_{c \to \infty} \sum_c IV_c^{R(\Delta \eta)} \Delta \zeta^{se}_{ct} + \lim_{c \to \infty} \sum_c IV_c^{R(\Delta \eta)} \left( \Delta \sum_l \eta_{jct} \epsilon_{ict} \right) = 0 \]

\[ \Rightarrow \lim_{c \to \infty} \sum_c IV_c^{R(\Delta \eta)} \Delta \zeta^{se}_{ct} + \lim_{c \to \infty} \sum_c \sum_l \Delta \eta_{cit} \varpi_{it-1} \left( \Delta \sum_j \eta_{jct} \epsilon_{jct} \right) = 0 \]

\[ \Rightarrow \lim_{c \to \infty} \sum_c IV_c^{R(\Delta \eta)} \Delta \zeta^{se}_{ct} + \lim_{c \to \infty} \sum_c \sum_l \Delta \eta_{cit} \varpi_{it-1} \left( \Delta \sum_j \eta_{jct} \epsilon_{jct-1} + \sum_j \eta_{jct} \Delta \epsilon_{jct} \right) = 0 \]

\[ \Rightarrow \lim_{c \to \infty} \sum_c IV_c^{R(\Delta \eta)} \Delta \zeta^{se}_{ct} + \lim_{c \to \infty} \sum_c \sum_l \Delta \eta_{cit} \varpi_{it-1} \Delta \sum_j \eta_{jct} \epsilon_{jct-1} \]
\[\Rightarrow \lim_{c \to \infty} \sum_c lV_c^{R(\Delta \eta)} \Delta \varepsilon_{ct}^{se} + \lim_{c \to \infty} \sum_l \sum_j \sum_c \left(\hat{\mu}_0 + \hat{\mu}_1 \eta_{ict-1} + \sum_x \hat{\mu}_2 \ln(Dist_{cx})\right) \Delta \eta_jct \varepsilon_{jct-1} \]

\[+ \lim_{c \to \infty} \sum_l \sum_j \sum_c \left(\hat{\mu}_0 + \hat{\mu}_1 \eta_{ict-1} + \sum_x \hat{\mu}_2 \ln(Dist_{cx})\right) \eta_jct \Delta \varepsilon_{jct} = 0\]

\[\Rightarrow \lim_{c \to \infty} \sum_c lV_c^{R(\Delta \eta)} \Delta \varepsilon_{ct}^{se} + \lim_{c \to \infty} \hat{\mu}_0 \sum_l \sum_j \sum_c \Delta \eta_jct \varepsilon_{jct-1} \]

\[+ \lim_{c \to \infty} \hat{\mu}_1 \sum_l \sum_j \sum_c \eta_{ict-1} \Delta \eta_jct \varepsilon_{jct-1} \]

\[+ \lim_{c \to \infty} \sum_l \sum_j \sum_x \sum_c \ln(Dist_{cx}) \Delta \eta_jct \varepsilon_{jct-1} \]

\[+ \lim_{c \to \infty} \hat{\mu}_0 \sum_l \sum_j \sum_c \eta_jct \Delta \varepsilon_{jct} \]

\[+ \lim_{c \to \infty} \hat{\mu}_1 \sum_l \sum_j \sum_c \eta_{ict-1} \eta_jct \Delta \varepsilon_{jct} \]

\[+ \lim_{c \to \infty} \sum_l \sum_j \sum_x \sum_c \ln(Dist_{cx}) \eta_jct \Delta \varepsilon_{jct} = 0 \quad (A.33)\]

The employment shares can be solved for in the model. A first-order linear approximation of the \(\eta_jct\) can be derived as:

\[\eta_jct \approx \frac{1}{I} + \vartheta_1 \left(\varepsilon_{jct} - \frac{1}{I} \sum_j \varepsilon_{jct}\right) \quad (A.34)\]

Based on (A.34), it can be seen that (A.33) at its core depends on independence of geographic distance measures from first, second, and third moments of \(\varepsilon_{jct}\), past and present. Hence, is the assumption of independence that includes these conditions.