# Effects of Shifts in Industrial Compositions on Wages in Developing Countries: The Case of Mexican Cities and NAFTA*

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**Abstract**

Industrial or trade policy changes often result in shifts in local industrial compositions. Such shifts are not necessarily similar sub-nationally everywhere within an economy. If there are further effects associated with shifts in industrial compositions, the heterogeneous patterns of local restructurings translate into heterogeneous patterns of further local impacts. *What happens to wages when local industrial composition of employment shifts?* Here, I address this question in the context of Mexican cities in the 1990s, the decade during which NAFTA was enacted. Using Mexican census data, I measure city compositions of sectoral employment and exploit geographical variation in this measure over time to see whether shifts in local sectoral compositions systematically affect local wages across all sectors within cities. Heterogeneities across cities in terms of the effects of the change in trade policy on their sectoral compositions are used to deal with concerns about endogeneity of the measure of industrial composition. The results indicate significant and large within-city wage effects causally associated with local changes in sectoral compositions of employment; i.e., controlling for the wage effect of induced changes in city-sector labour demands, cities with higher induced concentration of employment in higher paying sectors tend to have significantly higher growth in wages across all sectors. This effect is almost 4 times larger than the wage impact conventionally associated with shifts in industrial composition, which neglects general equilibrium effects. The results are robust to correcting for sample selection bias generated by regional migrations and to the presence of alternative explanatory mechanisms. The findings emphasize the need for policy-analysis approaches that take into account general equilibrium effects and address spatial heterogeneities. While induced pattern of shifts in local industrial compositions substantially improved the earnings of workers in majority of Mexican cities during the 1990s, in some cities mostly in South of Mexico due to a different pattern of induced shifts in industrial compositions, growth in workers' earnings actually decreased. The results may provide an explanation for the increase in North-South wage gap in Mexico.

Keywords: Industrial Composition, Wage Structure, NAFTA, Regional Development, Spatial Distribution of Policy Impacts, Mexico, Developing Countries, Trade Policy, Industrial Policy

JEL Classification: O18, R58, O24, R11, O25, J31, O54, O11, O12, R23

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## 1 Introduction

Industrial or trade policy changes may result in shifts in industrial compositions that are not necessarily the same in different regions sub-nationally. If there are further effects associated with shifts in industrial compositions, the heterogeneous patterns of local compositional restructurings translate into spatially heterogeneous ultimate local impacts. *What happens to wages when local industrial composition of employment shifts?* Beaudry et al. (2007) address this question in the context of the U.S. cities during 1970-2000 and find substantial general equilibrium wage effects associated with shifts in industrial composition. Here, as an extension of their results to the case of the developing countries, I intend to study wage effects of policy induced shifts in industrial compositions in Mexico.

In this paper, I address the question posed above in the context of Mexican cities during the 1990s, the decade during which NAFTA was enacted. Using Mexican census data, I measure city compositions of sectoral employment, as employment-share weighted sum of national sectoral wage premia, and exploit geographical variation in this measure over time to see whether there is general equilibrium effects associated with shifts in local sectoral compositions that systematically affect local wages across all sectors within cities.

The results indicate significant and substantial within-city general equilibrium wage effects causally associated with local changes in sectoral composition of employment; i.e., controlling for the wage effect of induced changes in city or city-sector labour demands, cities with higher induced concentration of employment in higher paying sectors tend to have significantly higher growth in wages across all sectors. The magnitude of the general equilibrium wage effects found here is almost 4 times as big as the wage effect conventionally associated with shifts in industrial compositions, which neglects general equilibrium effects. A shift in a city's industrial composition that increases its measure by 0.01 units, would as a result of the general equilibrium effects identified here increase sectoral wages in that city by about 4%, holding the city-sector employment rates (i.e., the demand effect associated with the change in industrial composition) constant. The estimates do not suffer from endogeneity and are robust to correcting for sample selection bias generated by regional migrations within Mexico, and to the introduction of alternative explanatory mechanisms.

It is important to emphasize that the relationship discussed here is about the general equilibrium wage effects that are associated with shifts in the composition of demand for labour rather than changes in overall demand. In fact, in estimating the relationship of interest, I control for the wage effects induced by changes in overall city demand or city-sector demands for workers by including proper employment rates in the right-hand-side of estimation equations.

The findings accentuate the need for policy-analysis approaches that take into account general equilibrium effects and address spatial heterogeneity of policy impacts across regions and localities. It is shown here that in Mexico during the 1990s there were general equilibrium wage effects associated with shifts in local industrial compositions. Further, it is shown that induced shifts in local industrial compositions are not the same in different localities. As a result, while in majority of Mexican cities the induced shifts in local industrial compositions favoured higher paying sectors and substantially improved the earnings of workers during the 1990s, in some cities mostly in South of Mexico, as a result of different pattern of induced local shifts in structure of employment, growth in workers' earnings actually decreased. Such results indicate an increase in the North-South wage gap in Mexico during the 1990s. The findings here may explain the observed growing wag gap in Mexico (Hanson, 2005b; Chiquiar & Hanson, 2007).

An example would make this point clearer. During the ten years from 1990 to 2000, in San Francisco del Rincón metropolitan area in central Mexico measure of sectoral composition of employment increased about 0.035 units. This was mainly due to large movements of labour force into Manufacturing and out of Agriculture, which respectively pay the 7$^{th}$ highest and the lowest wages amongst the 15 sectors in Mexico. During the same period, wages in the Agriculture in this city increased by almost 16%. A general equilibrium wage impact of the magnitude found in this study implies that about 13.3% of such wage increase this city is caused by the specific pattern of change in sectoral composition of employment in this city. In other words, in the absence of such impacts from shifts in the sectoral composition of employment, wages in Agriculture in this city would have increased by only 2.7%. This is while in Minatitlán in southern Mexico the measure of sectoral composition of employment decreased by about 0.054 units mainly due to large movements of workers out of the Mining and Manufacturing sectors into the low paying sectors such as Agriculture, Private Household Services, Whole Sale and Retail Trade, Hotels and Restaurants, and Education. Given the general equilibrium wage effects found here, it is no surprise that Agriculture wages in this city decreased during the decade by about 28%. About 21% of this change is caused by the wage effect of the specific pattern of shift in industrial composition in this city.

Often the aggregated national restructurings are not representative of the induced changes at sub-national levels. For example, formation of the maquiladoras as a result of industrial policies since the mid-1960s combined with trade liberalizations implemented by Mexico during the late 1980s 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 Mexico as well. Graphs (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 corresponding changes in Border, Northern, and Central regions, in South the pattern seems to be different. This is clearer in Graph (1.3) where now the metropolitan area that includes Mexico City is dropped from the central region. Graphs (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 Real Estate and Business Services sector represents the associated regional changes, again in Manufacturing the pattern is very much different at the national and regional levels; Manufacturing's 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. If there are further effects associated with shifts in industrial compositions (e.g. on wages, growth, poverty, inequality, etc.), then the ultimate impacts would have to be different in regions with different patterns of shifts in industrial compositions.

In this study, I employ the outcome of the theoretical model in Beaudry et al. (2007) and use the data provided by IPUMS-International[1] to study inter-sectoral wage spillovers associated with good jobs in Mexican metropolitan areas during 1990-2000. Beaudry et al. (2007) construct a theoretical search and bargaining model of a labour market that incorporates a general equilibrium channel through which changes in industrial composition of employment can cause impacts on wages in all sectors. In their model, when an unemployed worker is matched with a firm in a specific sector, they start bargaining over the wage. Unemployed workers use their outside option as leverage for bargaining. The outside option is to leave the match and search for jobs. The value of this option depends on the distribution of employment opportunities as it is assumed that an unemployed worker finding a job in another industry will find it in proportion to

[1] IPUMS-International, a project in the Minnesota Population Centre Data Projects at www.ipums.umn.edu, is to be highlighted as the provider of the data used in this study.

the relative size of that industry in the city. Thus, it turns out that improvements in composition of employment in a city in favour of the higher paying sectors so that employment share of such sectors increase in the city's total employment is an improvement in the value of the outside option of the bargaining unemployed workers in all sectors within the city and will consequently result in higher wages across all sectors. Their estimate of the average such impacts from shifts in industrial composition on wages for the case of U.S. cities during 1970-2000 finds it to be substantial and persistent. The magnitude of their estimates is about 3.5 times larger than the conventional composition-adjustment approach that neglects general equilibrium effects compared. My estimate of the same effects for the case of Mexican cities in the 1990s is about 4 times larger than the conventional composition-adjustment approach.

Mexico in the 1990s is an interesting case study for the purpose of this paper due to policy changes and economic events that took place during and just before this decade. 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 continued 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 (see Ros, 1994). 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 stepped into an economic crisis. Although recovering from it was relatively fast (Kose et al., 2004), Mexico nevertheless suffered from its impacts (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 Jordaan, 2008; Aydemir and Borjas, 2007; Chiquiar & Hanson, 2007; Richter, Taylor, and Yúnez-Naude, 2005; Hanson, 2005a and 2005b; Chiquiar, 2005; Tornell, Istermann, and Martinez, 2004; Hanson, 2003; Hanson, 1998) [2], all of which have made the Mexico of the 1990s a suitable case study for the purpose of this paper.

In estimating the wage effects of shifts in local industrial compositions heterogeneities across different cities in Mexico in terms of the effects of the change in trade policy during the 1990s on their sectoral compositions are used to deal with the concerns about endogeneity of the measures of industrial composition and employment rates. Intuitively, the source of endogeneity

[2] None of the works cited here consider the possibility of general equilibrium effect associated with shifts in the composition of demand for labour. The impact of the change in trade policy on wages could be much larger as a result of such effects.

is a reflection problem that is hidden behind the question addressed in this study in a general equilibrium setting: a shift in a city's industrial composition translates into a shift in employment-share weighted average of wages in that city, which affects sectoral wages in the city due to the general equilibrium mechanism, which in turn result in further changes in the average wages. In other words, the wage in one sector appears on both sides of the estimating equations. This is likely to affect the OLS estimations since the measure of industrial composition used here, constructed as employment-share weighted sum of national sectoral wage premia, is a proxy for the city average wages. Thus, an instrumental variable strategy in necessary to make sure of the consistency of the OLS estimates.

As explained before, the enactment of NAFTA falls in the middle of the period of this study. The initial year of study (1990) is 4 years before enactment of NAFTA in 1994 and the ending year of the study (2000) is 6 years after the enactment of NAFTA. During this period and as a result of NAFTA, the US became an ever more important trade partner for 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.[3] This is while ground transportation using trucks was 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[4]. Hence, 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). Cities' region and distance from the US border are thus used as instrumental variables to deal with the possible endogeneity of the change in the measure of industrial composition. This instrumental variable approach implies that the causal relationship identified here is in fact the wage effects of shifts in industrial compositions that are induced by the change in trade policy and enactment of NAFTA. The results of the instrumental variable estimation indicate that the OLS estimates are unlikely to suffer from endogeneity.

Estimates of the relationship of interest are robust to correcting for the sample selection bias that is caused by the migration of workers across cities within Mexico. Although it is verified

[3] 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.

[4] U.S. Department of Transportation, Research and Innovative Technology Administration, Bureau of Transportation Statistics, Trans Border Freight Data, accessed via http://www.bts.gov/programs/international/transborder/TBDR_QA.html on September 21, 2009.

that the sample suffers from selection bias, after correcting for it according to the approach in Dahl (2002), the estimates of the effects of changes in industrial compositions on wages remain significant and do not significantly change in magnitude. The findings are also shown to be robust in significance and size to the introduction of other alternative explanations 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 (Moretti, 2004; Acemoglu and Angrist, 1999), and minimum wages (Fairris, Ropli, and Zepeda, 2008). Introducing the education levels in the form of average years of schooling gives an interesting side observation; an estimate for the social return of increase in education at the city level. City level social return of education in Mexico seems to be at least about 8% and is marginally significant (at 10% level of significance). In other words, adding one year to the average years of schooling in a city in Mexico would increase wages paid in all sectors within that city by 8%.

The paper is structured as follows. Section 2 briefly reviews the theoretical model and takes away a guideline that forms the empirical strategy discussed in section 3. Section 4 explains the data, section 5 reports the estimation results, and section 6 concludes.

## 2 Theory

In this section, I briefly explain the theoretical model in Beaudry et al. (2007) that provides me with structural relationships used here as a guide in the empirical section.[5] The model shows how in a general equilibrium search and bargaining framework a change in industrial composition of employment affects sectoral wages, even in sectors that are not part of the change. As in any search model, when a worker is matched with a firm in a specific sector, they start bargaining over the wage. Workers use their outside option as leverage for bargaining. The outside option is the likelihood of leaving a sector to find a job in other sectors that pay higher wages. If composition of employment in a city changes in favour of the higher paying sectors, it is an improvement in the outside option of unemployed workers bargaining and results in higher wages in all sectors. Whether this composition effect is sizable or not is of course an empirical question.

It is important to note that such wage effects (spillovers) are different from the overall demand effects in the economy. In the event of a shift in sectoral composition of employment in

[5] See the appendix for in-detail reproduction of the model in Beaudry et al. (2007).

a local economy, one would expect impacts on local wages due to respective changes in city-sector demands for labour. However, the model used here shows that even holding the city-sector employment rates constant, shifts in sectoral composition of employment impacts wages in all sectors.

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 weigh 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 to produce a sector specific product sold at a sector specific price. In the same way as firms, individuals compare the discounted expected benefits from being unemployed with being an employee and receiving the city-sector wages. As mentioned before, there is a random matching process through which workers are matched with firms and, as usual, in 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 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 well 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 profits earned and costs of creating vacancies within each sector. In equilibrium all the variables of the model, including industrial compositions of cities, are functions of these exogenous city-sector advantage terms and this will be the source of a likely endogeneity at the time of estimation as these city-sector advantage terms appear in the residuals.

Without going into the details, solving the model for city-sector wages gives the following equilibrium relation:

$$w_{ic} = \gamma_{c0} + \gamma_{c1} p_i + \gamma_{c2} \sum_j \eta_{jc} \, w_{jc} + \gamma_{c1} \epsilon_{ic}, \qquad (1)$$

where $w_{ic}$ is city $c$ sector $i$'s specific wage, $p_i$ is price of the sector specific product, $\eta_{jc}$ represents the fraction of city $c$'s vacant jobs that are in sector $j$, and $\epsilon_{ic}$ is the exogenous advantage of city $c$ in terms of the performance (profits) in sector $i$. The parameters in this equation are all implicit functions of city-sector employment shares, city level employment ratios, a measure of the bargaining power of the workforce, and exogenous city-sector performance cost 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 (for more details on the classic reflection or social interaction problem see Manski (1993) and Moffitt (2001)). According to equation (1), increase in wages in one sector increases the average wage in city, and the latter would increase wages in all sectors in the city as a result of the bargaining mechanism and improvements in the outside option of unemployed workers. This will be a source of endogeneity in estimating this equation. The strength of this strategic complementarity is captured by $\gamma_{c2}$. 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), a pure shift in sectoral composition that causes a one unit increase in the average city wage, $\sum_j \eta_{jc} w_{jc}$, increases the within sector wages by $\gamma_{c2}$ in all sectors. But these increases in all within sector wages cause the average wage to increase by another $\gamma_{c2}$ units, inducing a further round of adjustments. The total effect of the pure change in sectoral composition on the average wage would therefore be $\frac{1}{1-\gamma_{c2}}$.

The reflection problem inherent in equation (1) due to $w_{ic}$ appearing on both side of the equation, causes an issue of simultaneity so that increases in average wages will impact wages in sector $i$ but at the same time this will increase the average wages again. To deal with the simultaneity inherent in equation (1), and to directly show the impact of employment rate, manipulation[6] of this equation results in the following equation:

[6] Taking linear approximation at the point where cities have identical sectoral composition ($\eta_{ic} = \eta_i = 1/I$) and employment rates ($ER_c = ER$), which arises when there is no city-sector advantages in the model, and assuming similar matching probabilities across cities and sectors so that all the $\gamma$ coefficients are nothing but the average of $\gamma_c$'s across cities at these similar matching probabilities.

$$w_{ic} = d_i + \frac{\gamma_2}{(1-\gamma_2)} \sum_j \eta_{cj} \left(w_j - w_1\right) + \gamma_{i5} ER_c + \xi_{ic}, \qquad (2)$$

where $d_i$ is the 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[7] 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 effects of a tighter labour market may affect the bargaining power of firms in a sector with a high value-added product differently from the bargaining power of firms in a sector with a low value added product.

Equation (2) shows how city-sector wages depend on the sectoral composition of a city's employments captured by the term $\sum_j \eta_{cj} \left(w_j - w_1\right)$. I will denote this term by $R_c$ and refer to it as *the measure of industrial composition*[8]:

$$R_c = \sum_j \eta_{cj} \left(w_j - w_1\right). \qquad (3)$$

Differencing the structural equation in (2) within a city-sector cell across two steady state equilibria, gives the following estimating equation:

$$\Delta w_{ic} = \Delta d_i + \frac{\gamma_2}{(1-\gamma_2)} \Delta R_c + \gamma_{i5} \Delta ER_c + \Delta \xi_{ic}, \qquad (4)$$

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.

[7] 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.

[8] Notice that a high value for the measure of industrial composition indicates that the city's employment is concentrated in higher paying sectors.

In this study I am interested in estimating the coefficient on the changes in the measure of industrial composition in (4); $\frac{\gamma_2}{(1-\gamma_2)}$. 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 the measure of industrial composition on within sector wages, as opposed to $\gamma_2$, which provides the partial unidirectional effect.

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 that sector have better outside options to use when bargaining with firms in cities with higher rents (cities with a distribution of employment more in favour of higher paying sectors).

Endogeneity of the variables in the estimating equation (4) puts the success of the identification strategy in danger. As explained before, one source of endogeneity here is the kind of city wide overall improvements that cannot be controlled for and 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 (4). As far as the change in measure of industrial composition is concerned, the requirement for OLS to give consistent estimates of the coefficients in (4) can be expressed as follows:

$$\operatorname*{plim}_{C,I\to\infty} \frac{1}{I}\frac{1}{C}\sum_{i=1}^{I}\sum_{c=1}^{C}\Delta R_c \Delta\xi_{ic} = \operatorname*{plim}_{C,I\to\infty} \frac{1}{I}\frac{1}{C}\sum_{c=1}^{C}\Delta R_c \sum_{i=1}^{I}\Delta\xi_{ic} = 0, \qquad (5)$$

recognizing that a similar condition is required for the change in employment rate. Given that this 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 $\epsilon_{ic}$. 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.

It can be shown that an instrumental approach could be devised to consistently estimate the parameters in (4) if the $\epsilon$'s are assumed to follow a random walk process – i.e., if the increments are independent of the past. Intuitively, under the random walk assumption the residuals in (4) aggregated at the city level (averaged across sectors within each city) are independent of past values. Thus, for example, a useful instrumental variable could be a suitable function of the initial period local employment shares that varies only across cities and is highly correlated with the changes in the measure of industrial composition. The decomposition of changes in the measure of industrial compositions into two parts, one based on changes in the city-sector employment shares and the other based on changes in the national wage premia, will be used as a guide in choosing the suitable functional form in generating the instruments[9]. Chapter 3, section 3.1 presents a more detailed exposition of generating instruments. A detailed discussion of the source of the endogeneity and the assumptions required for the OLS or IV approach to work are left for section 3.2 below.

# 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 estimation of the relationship between the measure of industrial composition and city-sectoral wages. Briefly, the empirical strategy here is to explore geographical variation of changes in the measure of industrial composition over two far enough points in time to see whether changes in city-sector wages are systematically related to the shifts in local industrial compositions. Several preliminary steps are required to prepare the data for estimating the ultimate relationship of interest. Also, endogeneity and sample selection bias are potential issues that may jeopardize the success of the estimation strategy. This section explains the preliminary steps and addresses several estimation issues.

The empirical estimating equation that closely matches equation (4) is specified as:

$$\Delta w_{cit} = \Delta d_t + \Delta d_{it} + \beta \Delta R_{ct} + d_i \times \Delta ER_{ct} + \Delta \xi_{cit} \,. \qquad (6)$$

Since the data used in this study is only available for two distinct points in time ten years apart from each other, $\Delta d_t$, the change in time dummy, becomes a constant playing the role of an intercept and $\Delta d_{it}$, the change in sector-time dummies, becomes nothing but a full set of sector dummies excluding the base sector. The left hand side variable is the time change in wages paid

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[9] $\Delta R_c = \Delta \sum_j \eta_{cj} \cdot (w_j - w_1) = \sum_j \Delta\eta_{cj} \cdot (w_j - w_1) + \sum_j \eta_{cj} . \Delta(w_j - w_1) = \Delta \mathrm{R}_c^1 + \Delta \mathrm{R}_c^2$

in sector $i$, city $c$, $\Delta R_{ct}$ is the change in the measure of industrial composition over time, $d_i \times \Delta ER_{ct}$ is the cross product of change in city employment rate over time and sector dummies or changes in city-sector employment rates, and $\Delta\xi_{cit}$ is the error term.

The parameter of interest is $\beta$ that captures the relationship between the measure of industrial composition and city-sectoral wages while controlling for the impact of the overall demand for labour at city (captured by only including $\Delta ER_{ct}$ instead of its interactions with sector dummies) or city-sector level (captured by $d_i \times \Delta ER_{ct}$). In other words, in this specification the relationship captured by the estimates of $\beta$ is in isolation from the impact of overall demand at city or city-sector level on sectoral wages. In estimation of equation (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, one can disregard the inter-sectoral wage interactions in the process of wage determination in local economies. On the other hand, however, a statistically significant and sizable coefficient is indicative of a general equilibrium mechanism through which local sectoral composition of employment in each local economy has a significant impact on wages in all sectors in that economy. 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.

In equation (6) the measure of industrial composition is computed as the weighted sum of the national sectoral wage premia using city-sectoral employment shares as the weights:

$$R_{ct} = \sum_i \frac{e_{cit}}{\sum_i e_{cit}} \cdot \left(\frac{w_{it}}{w_{1t}} - 1\right), \qquad (7)$$

where $e_{cit}$ indicates employment in sector *i*, city *c*, in year *t*, $w_{it}$ indicates sector *i*'s *intrinsic* wage at the national level in year *t*, and in the same way $w_{1t}$ measures the intrinsic wage in sector one in the national economy. In (7), $\frac{e_{cit}}{\sum_i e_{cit}}$ 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 $(\frac{w_{it}}{w_{1t}} - 1)$. So, the measure of industrial composition is a proxy for average wages in a city and measures how much wage premium a city is generating given its distribution of employment across different sectors.

To illustrate how this way of measuring the industrial composition (using national rather than local wage premia) is useful, consider the following example. In a given year, between two otherwise similar cities, the one with higher concentration of employment in sectors that intrinsically offer higher wages is expected to have a higher measure of industrial composition. This is because national wage premia, rather than local wage premia, are used and wage realization in each city has an insignificant role in the construction of the measure of industrial compositions. Therefore, 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 the city with a higher measure of industrial composition. Of course, as explained before, if there are city wide improvements that systematically move the measure of industrial composition and wages together, because we cannot control for city fixed effects, the OLS estimates are no more reliable due the endogeneity of regressors. I will later explain that under some assumptions an IV approach can 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 data with no problem, but the national wage premia needs to be estimated. Comparing (7) with (3) one will notice that in (7) the formula has been modified by dividing the measure of industrial composition by $w_1$ to allow for using the log-wages in estimating the sectoral wage premia.[10] To empirically estimate the national wage premia in different sectors from the observed wage and employment data, the following specification is used and estimated separately for each year:

$$ln(W_{kci}) = \alpha + \boldsymbol{X}_k^{'}\boldsymbol{\gamma} + \sum_i \varpi_i d_i + \varepsilon_{kci}, \qquad (8)$$

where $W_{kci}$ is the observed wage received by person *k* in city *c* working in sector *i*, $\boldsymbol{X}_k$ denotes an array of the worker's attributes, $d_i$ indicates sector dummies other than the base sector, and *ln(.)* is the natural logarithm function. In equation (8), estimates of $\varpi_i$'s in each year by

[10] Since each local geographical region considered here is large enough to embody a complete labour market that encompasses all different sectors, the choice of the base sector is not of any significance in terms of affecting the ultimate relationship of interest.

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 (7):

$$R_{ct} = \sum_i \frac{e_{cit}}{\sum_i e_{cit}} \cdot \left(\frac{w_{it}}{w_{1t}} - 1\right) \equiv \sum_i \frac{e_{cit}}{\sum_i e_{cit}} \varpi_{it}. \qquad (9)$$

In (9) $\varpi_{it}$ is the coefficient of the respective sector dummy in equation (8) estimated for year *t*.

The next variable that requires attention is the left-hand-side variable in equation (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 *intrinsic* to the sector and city where they work.[11] 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 estimating equation can be considered as regression adjusted wages for the attributes of workers averaged across individuals within each city-sector cell:

$$ln(W_{kci}) = \alpha + \boldsymbol{X}_k^{'}\boldsymbol{\gamma} + \sum_c \sum_i w_{ci} d_{ci} + \omega_{kci}. \qquad (10)$$

Equation (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, which will be used as the left-hand-side variable in equation (6).

In the same way as city-sector employment shares, the city level employment rates can also be computed directly from the data. Having generated all the appropriate dependent and explanatory variables, equation (6) can now be estimated to see whether changes in sectoral composition of employment in Mexican cities systematically relay externalities on all local wages across all sectors. It remains in this section to address the concerns about endogeneity and sample selection as follows.

[11] Another way to interpret this, is to say that the model is for a person with given skill level.

## 3.1 Selection

In this section I try to address the issue of selection bias that the empirical strategy may suffer from. If in practice 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 (born there and not moved anywhere else or born somewhere else and moved to this city). This will compromise one of the conditions required for the consistency of OLS estimates of these regressions being the zero mean residual. In practice, in equations (8) and (10) I am actually dealing with a conditional residual mean term, conditioned on the wage figure being observable. For example, for equation (8) I can write:

$$E[ln(W_{kci})|\boldsymbol{X}_k,\ d_i, and\ W_{kci}\ being\ observed] \\ = \alpha + \boldsymbol{X}_k^{'}\boldsymbol{\gamma} + \sum_i \varpi_i d_i + E[\varepsilon_{kci}|\boldsymbol{X}_k,\ d_i, and\ W_{kci}\ being\ observed]. \qquad (11)$$

It is not clear if the conditional error mean term in (11) is actually zero in a self selected sample. 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 to us but related to the structure of wages ($\Delta\xi_{ic}$), the change in the measure of industrial composition in equation (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 I am interested in without it really existing. Thus, it is very important to adjust the empirical strategy to correct for this possibility. In addressing this issue, I implement the approach in Dahl (2002).

Dahl (2002) develops an econometric approach to correct for sample selection bias and answer why high rate of interstate migration has not led to equalized 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. He proposes a semi parametric methodology to correct for sample selection bias in such a choice model.

Dahl (2002) 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 (11) 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 (2002) approach to my setting, I can identify the mean error term as a function of relevant migration probabilities:

$$E[\varepsilon_{kci}|\boldsymbol{X}_k,\ d_i, and\ W_{kci}\ being\ observed] = \sum_b d_{kbc} \cdot f_{bc}(P_{kbc}, P_{kbb}) + \vartheta_{kci}\ , \qquad (12)$$

where $d_{kbc}$ is an indicator that takes one only if person *k* born in state b has actually moved to city *c*, $E[\vartheta_{kci}|\boldsymbol{\kappa}_{kci},\ d_i, and\ W_{kci}\ being\ observed] = 0$, and $f_{bc}(\cdot)$ is an unknown function of the probability that person *k*, born in state *b*, is observed in city *c* ($P_{kbc}$) and probability that person *k*, born in state *b*, remains in the same state ($P_{kbb}$). I choose function $f_{bc}(\cdot)$ to be quadratic in each of the probabilities separately. In this way, equation (8) can be written as:

$$ln(W_{kci}) = \alpha + \boldsymbol{X}_k'\boldsymbol{\gamma} + \sum_i \varpi_i d_i + \sum_b d_{kbc} \cdot f_{bc}(P_{kbc}, P_{kbb}) + \vartheta_{kci} \qquad (13)$$

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 (i.e., if city $c$ is in state $b$).

In the same way, equation (10) can also be corrected for selection:

$$ln(W_{kci}) = \alpha + \boldsymbol{X}_k'\boldsymbol{\gamma} + \sum_c \sum_i w_{ci} d_{ci} + \sum_b d_{kbc} \cdot f_{bc}(P_{kbc}, P_{kbb}) + \varsigma_{kci}, \qquad (14)$$

where $E[\varsigma_{kci}|\boldsymbol{X}_k,\ and\ W_{kci}\ being\ observed] = 0$.

In a given city $c$, the identification for the movers ($P_{kbc}$) comes from the variation in the state of birth and 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.

## 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 in section two above 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 (6) relies partly[12] on the following condition:

$$\underset{C,I\to\infty}{plim}\frac{1}{I}\frac{1}{C}\sum_{i=1}^{I}\sum_{c=1}^{C}\Delta R_c\Delta\xi_{ic} = \underset{C,I\to\infty}{plim}\frac{1}{I}\frac{1}{C}\sum_{c=1}^{C}\Delta R_c\sum_{i=1}^{I}\Delta\xi_{ic} = 0,$$

where from the theoretical part $\Delta\xi_{ic} = \gamma_1\Delta\epsilon_{ic} + \gamma_1\frac{\gamma_2}{1-\gamma_2}\sum_j\frac{1}{I}\Delta\epsilon_{jc}$ . Following Beaudry et al. (2007) city-sector performance advantage terms can always be decomposed as $\epsilon_{ic} = \hat{\epsilon}_c + \upsilon_{ic}^{\epsilon}$ into absolute city advantage, $\hat{\epsilon}_c$, and comparative city-sector advantage term, $\upsilon_{ic}^{\epsilon}$, where by definition $\sum_i\upsilon_{ic}^{\epsilon} = 0$. The condition above depends primarily on properties of the absolute advantage component $\hat{\epsilon}_{ct}$. It can be shown that the condition for *consistency of OLS estimates relies on the assumption that absolute advantages are independent of comparative advantages in all periods* (see the appendix for details). 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

[12] A similar condition is required for the employment rate, $\Delta ER_c$.

particular pattern of sectoral structure. Since I cannot control for city fixed effects and this condition may not hold, using instrumental variables is necessary to be able to consistently estimate equation (6).

*Under a weaker assumption that changes in the absolute advantages are independent of the initial set of comparative advantage factors for that city – i.e., sufficiently if absolute advantages follow a random walk process with increments independent of past values – an instrumental variable approach can be devised*. Beaudry et al. (2007) use national level observations on growth in sectoral employment shares to predict city level employment shares and construct their instruments. Essentially, they ask what the change in the measure of industrial composition would be if employment in each sector within the cities had grown at the same rate as national level employment in that sector. Notice that for each given industry they essentially use one growth rate of sectoral employment for all cities; the national growth rate of employment for that given industry. Thus, to the extent that the assumption required for validity of their instruments is reasonable and to the extent that their re-constructed changes in the measure of industrial compositions based on the growth rates of national sectoral employment do a good job in mimicking the actual changes in the measure of industrial compositions, they are able to deal with the endogeneity of the measure of industrial composition.

Here, however, I will explore a set of instruments that may be more relevant to the context of this study. Essentially, I will predict different growth rates of employment in different cities for a given sector based on perceived effects of the change in trade policy during the 1990s on cities on the basis of the distance of cities from the U.S. border. Specifically, I use the region the city is located in (Border, Northern, Central, and Southern), the minimum distance of Mexican cities from the U.S. border, and the interaction of these two variables as instruments for changes in the measure of industrial composition and changes in city employment rates in the first stage. The validity of this group of instruments relies on the assumption that wage determination processes at each city are independent of the city's distance from U.S. border. In addition, I will use the minimum distance from border to predict growth rates of sectoral employments in different cities and construct nonlinear functions of these fitted values as instruments. Due to specific functional forms that will be used (explained below), validity of this group of instruments relies as well on the same weaker assumption mentioned before that the city absolute advantage terms follow a random walk process with increments independent of past values. Of course, the question at this point is about the reason why distance from border and region are valid and relevant instruments.

Briefly, during the 1990s the U.S. became an ever more important trade partner of Mexico, especially with the enactment of the North American Free Trade Agreement (NAFTA) between Canada, the U.S., and Mexico. With the surface transportation as the main mode of transportation between the U.S. and Mexico, minimum distance of Mexican cities from the U.S. border and region becomes relevant in understanding the distributive (heterogeneous) impacts of U.S.-Mexico trade across different regions and cities within Mexico. Therefore, by using distance from border and region, I will estimate the relationship between the measure of industrial composition and city-sectoral wages to the extent that changes in the measure of industrial compositions are induced by changes in the trade policy and to the extent that distance from border and region are relevant for understanding the distributive impacts of such a policy change within Mexico (see Hanson, 1998).

To what extent is the assumption required for validity of instruments reasonable? 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 sectors within that city over time. In other words two cities with approximately similar distance from border but located at opposite sides of the country are not expected to necessarily have similar wages in one industry or experience the same wage growth trajectories. However, it is possible that for the reason of choosing a specific time period, that of opening up to trade with the U.S., distance from border or region are suspected to have become relevant factors in part in the wage determination process in different sectors within cities. While being close to the capital city or other major cities was an advantage before the enactment of NAFTA, in its aftermath being close to the border might have become an advantage. Nevertheless, as far as the wage determination process is concerned, what is conceived as advantage in cities closer to the border is only because of the distributive demand and supply effects of trade with the U.S. across different regions and cities, which should affect the wage determination process through demand and supply of labour in cities and sectors (e.g. as a result of firm relocations and worker migration) and these are controlled for by the changes in the measure of industrial composition and employment rate in equation (6) and by correcting for selection bias as explained before. In other words, if there is a relationship between region or distance from border and changes in city-sectoral wages, it should be through mechanisms that are already controlled for by the measure of industrial composition and employment rates in equation (6).

To what extent are distance from border and region relevant? In short, in the aftermath of NAFTA, the U.S. became an ever more important trade partner for Mexico. With most of the trade between the U.S. and Mexico being transported using trucks, distance from border becomes an important factor in determining the distribution of impacts from NAFTA across different regions in Mexico.

Mexico has a long history in implementing different economic policies on its path to industrialization and integration into the international economy. The macroeconomic, industrial, and trade policies of the import-substitution era of the 1960s gave place to the export-oriented policies of the 1970s and later to the substantial liberalization of the economy in the late 1980s, which continued throughout the 1990s. Mexico entered the General Agreement on Tariffs and Trade (GATT) in August 1986, which was the starting point of a major trade and investment liberalization of the economy, and in November 1993 signed the North American Free Trade Agreement (NAFTA), which came to effect on January 1st 1994 (For details see Ros, 1994). The trade liberalizations of the late 1980s and early 1990s, restructured the Mexican economy in a heterogeneous fashion across different regions and different sectors and industries in the country. These restructurings had major impacts on wages[13] and reallocation of the Mexican work force across different regions and sectors during the 1990-2000 period (among others see Jordaan, 2008; Aydemir and Borjas, 2007; Richter, Taylor, and Yúnez-Naude, 2005; Hanson, 2005a and 2005b; Chiquiar, 2005; Tornell, Istermann, and Martinez, 2004; Hanson, 2003).

The initial year of the current study (year 1990) is four years before the enactment of NAFTA on January 1994, and the ending year of the study (year 2000) is six years after the enactment of the NAFTA. As mentioned above, during this period the US became an ever more important trade partner for 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.[14] 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

[13] None of the works cited here consider the possibility of general equilibrium effect of the forms discussed in this paper. The impact of the change in trade policy on wages could be much larger as a result of the general equilibrium effects associated with induced shifts in local industrial compositions.

[14] 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.

percent[15], indicating that the cost of transportation, hence distance from US border and region, are likely relevant candidates for understanding how changes in trade policy (Mexico Signing onto NAFTA) could have affected different cities and different sectors differently.

I should explain how the second group of instruments as non-linear functions of distance from border are constructed. These 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 ($\Delta R_{ct}^1$ below) and another that captures the changes resulting from variations in national level wage premia of sectors ($\Delta R_{ct}^2$ below):

$$\begin{aligned}\Delta R_{ct} &= \sum_i \eta_{cit+1}\varpi_{it+1} - \sum_i \eta_{cit}\varpi_{it} \\ &= \sum_i \eta_{cit+1}\varpi_{it+1} - \sum_i \eta_{cit+1}\varpi_{it} + \sum_i \eta_{cit+1}\varpi_{it} - \sum_i \eta_{cit}\varpi_{it} \\ &= \sum_i (\eta_{cit+1} - \eta_{cit})\varpi_{it} + \sum_i \eta_{cit+1}(\varpi_{it+1} - \varpi_{it}) = \Delta \mathrm{R}_{\mathrm{ct}}^1 + \Delta \mathrm{R}_{\mathrm{ct}}^2, \qquad (15)\end{aligned}$$

Each decomposition works like a manual for constructing instruments; IV1 based on $\Delta R_{ct}^1$ and IV2 based on $\Delta R_{ct}^2$:

$$IV1 = \sum_i (\hat{\eta}_{cit+1} - \eta_{cit})\varpi_{it}, \qquad (16)$$

$$IV2 = \sum_i \hat{\eta}_{cit+1}(\varpi_{it+1} - \varpi_{it}), \qquad (17)$$

where $\eta_{cit} = \frac{e_{cit}}{\sum_i e_{cit}}$, $\hat{\eta}_{cit+1} = \frac{\hat{e}_{cit+1}}{\sum_i \hat{e}_{cit+1}}$, $\varpi_{it}$ is the wage premium in sector *i* at the national level, and $\hat{e}_{cit+1} = e_{cit}(1 + g_{ic})$ with $g_{ic}$ being the fitted values from the following regression:

[15] U.S. Department of Transportation, Research and Innovative Technology Administration, Bureau of Transportation Statistics, Trans Border Freight Data, accessed via http://www.bts.gov/programs/international/transborder/TBDR_QA.html on September 21, 2009.

$$\Delta ln(e_{cit}) = \theta_0 + \sum_j \theta_{1j} \left( mindist_c \times d_j \right) + err., \qquad (18)$$

where $e_{cit}$ is sector $i$'s employment in city $c$, in year $t$, $mindist_c$ is the minimum distance of city $c$ from the U.S. border (or the distance from the closest major border-crossing point), $err.$ is the error term, and *ln(.)* is the natural logarithm. The fitted values from (18) would generate city-sector growth rates that only depend on the distance of cities from the border, which can be denoted $g_{ic}$ and used as shown above to generate IV1 and IV2.

The equality between OLS and IV estimates will be indicative of two important points: that OLS is consistently estimating the coefficients in (6) and that the stronger condition required for consistency of OLS is valid in the data (in other words, absolute advantages in a city are independent of comparative advantages in all periods). Of course these results are to the extent that the assumptions required for validity of the instrumental approach are satisfied in the sample.

It remains to address the concerns about the omitted variable bias given the existing alternative hypothesis in the literature regarding wage determination in cities. To make sure that the OLS estimates are robust at the presence of alternative explanations for differences in wages across cities such as those related to city size, education levels (Moretti, 2004; Acemoglu and Angrist, 1999), and diversity of employment in a city (Glaeser, Kallal, Scheinkman, and Shleifer, 1992), additional variables representing these alternative hypotheses will be added to equation (6).

Before moving to the estimation results in the next sections, it is important to mention that similar to $\Delta R_{ct}$, $\Delta ER_{ct}$ is also likely to be endogenous as explained before. To deal with the endogeneity of this variable, in addition to using distance from border and region and the interaction of these two, I follow an approach similar to Blanchard and Katz (1992). Specifically, $\sum_i \eta_{cit-1}\, g_{ic}$ is used as an instrument, were as before $g_{ic}$ is the predicted growth rate of employment in industry $i$, city $c$, using minimum distance from U.S. border. It can easily be shown that under the same weaker assumption required for the consistency of other functional instruments, this instrument is also valid.

# 4 Data

The data used here are extracted from the eleventh and twelfth Mexican General Population and Housing Census for years 1990 and 2000, originally produced by the Mexican National Institute of Statistics, Geography, and Informatics[16] 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 with identified level of education and positive monthly income, who are living in a metropolitan area. Since it is necessary in this study to define geographic limits of the local labour markets, the 2004 definition of metropolitan areas in Mexico (Secretaría de Dessarollo Social, Consejo Nacional de Pabloción, Instituto Nacional de Estadística, Geografía, e Informática, 2004) is utilised (see Figure 4.1).

Confining the sample only to the municipalities that are part of a metropolitan area reduces the size of the sample in terms of individual observations by 36.05% in 1990 and by 47.20% in 2000. After considering all the necessary constraints for cleaning the data, among the employed, from total observations of 878,792 for 1990, women form 30.7% of the sample and from a total of 947,089 observations in 2000, women form 34.8% of the sample. Some further sample statistics are presented in table (4.1).

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

[16] Instituto Nacional de Estadística, Geografía, e Informática (or INEGI in short)

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.

It was possible to carry out the empirical part by adjusting the monthly income using the hours of work (HRSWRK1) and work with weekly or hourly measures of income. However, in addition to the fact that benefits of doing so or the disadvantages of using monthly income are not clear, according to the IPUMS[17] the values recorded for hours of work in years 1990 and 2000 are implausibly high for some observations and this makes the calculation of weekly or hourly incomes very imprecise. Therefore, I have not used the hours of work to adjust monthly incomes to incomes for shorter periods.

Using the data on years of schooling (YRSCHL) seven categories of educational attainment are constructed the list of which is reported in table (4.1). Using the same variable and the age variable, 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 enables us to distinguish between foreign and domestic immigration. In addition, the information on whether an individual speaks an indigenous language allows us to control 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. 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 (4.1).

# 5 Estimation Results

This section describes the estimation results. Table (5.1) reports the pre first-stage regression which tries to explain the relationship between growths in employment in each sector in different cities (approximated by change in natural logarithm of city-sectoral employment over the decade 1990-2000) based on the minimum distance of cities from U.S. border. This regression is used to

[17] https://international.ipums.org/international-action/variableDescription.do?mnemonic=HRSWRK1 under 'Comparability – Mexico'.

predict the city-sector growth rates of employment that are induced by the distributive impacts of NAFTA across different cities and sectors as perceived according to the distance of each specific city-sector from the U.S. border. While employment growth in Mining, Construction, Wholesale and Retail Trade, Transportation and Communication, Public Administration and Defence, Education, and Health and Social Work sectors in Mexico do not seem to have a relationship with distance from border, employment growth in sectors such as Agriculture, Fishing, and Forestry, Manufacturing, Electricity, Gas, and Water, and Financial Services and Insurance was smaller in cities farther away from the border. This is while employment growth in Hotels and Restaurants, Real Estate and Business Services, and Private Household Services sectors were higher further south.

## 5.1 Baseline Estimation Results

Table (5.2) reports the results of various estimation techniques applied to equation (6). The first four columns are the OLS results and the rest of the columns are for IV estimations using the instruments explained in section three and presented here again:

$$Group\ 1 = \begin{cases} min\_dist \\ region \\ min\_dist \times region \end{cases}$$

$$Group\ 2 = \begin{cases} IV1 = \sum_i (\hat{\eta}_{cit+1} - \eta_{cit})\varpi_{it} \\ IV2 = \sum_i \hat{\eta}_{cit+1}(\varpi_{it+1} - \varpi_{it}) \\ IV_{ER} = \sum_i \eta_{cit-1}\, g_{ic} \end{cases}$$

The OLS results, which are reported for two different specification of equation (6), one with city employment rates as a control variable under OLS (1) and one with city-sector employment rates under OLS (2) in table (5.2), 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. Graph (5.1) depicts a scatter diagram of the controlled[18] variation in the change in city-sector wage versus controlled variation in the change in the measure of industrial composition. At the first look, it appears that the results of the OLS may be driven by the outlier on the top right corner of the scatter diagram, which is actually a data point belonging to Real Estate and Business Services sector in San Francisco del Rincon metropolitan area. However, re-estimating the equation after removing the data point belonging to this city and sector provides a slightly smaller estimate which is still highly significant (see the bottom left corner of the graph). Looking at a similar scatter diagram for this new regression, graph (5.2), there seems to be another outlier belonging to Mining sector in Nuevo Laredo metropolitan area. Dropping the associated observations and repeating the estimation will not change the magnitude of the estimate which is still highly significant (see the bottom left corner of the graph). Thus, the OLS results are not driven by any outlier city or sector observation. Also, given that the metropolitan area that includes Mexico City (Valle de Mexico) has a concentration of most of the sectors in comparison with other areas, I re-estimated equation (6) by dropping this metropolitan area from the sample, the results of which are not reported here. Doing so will not change the estimates reported under columns OLS (1) and OLS (2) in table (5.2) almost at all.

If OLS consistently estimates the relationship between the sectoral employment distribution and wages within cities, which relies on a set of assumptions as reviewed in previous sections (and in detail in the appendix), the fact that the coefficient of $\Delta R_c$ is positive and statistically significant is indicative of very important and interesting points. First, as explained in the previous sections, a statistically-different-from-zero estimate supports the existence of the mechanism through which sectoral employment composition of cities have a causal impact on local sectoral wages.

Secondly, the general equilibrium impact of a shift in industrial composition is almost four times the conventional accounting measure of such a shift. The conventional accounting approach measures the effect of a shift in industrial composition by keeping wages fixed, i.e., by ignoring the further changes in wages caused by the initial change in average wage resulting from the shift in industrial composition. As explained in section two under equation (1), $1/(1-\gamma_{c2}) = 1+\gamma_{c2}/(1-\gamma_{c2})$ is the total wage impact of a change in industrial composition

[18] 'Controlled' here means that the effect of changes in sectoral demand for workers (change in the sectoral employment rates) are taken out of the variation in the variable of interest. For the case of changes in wages, the residuals in the regression of changes in city-sector wages on changes in sectoral employment rates give the controlled version of the change in city-sector wages.

that changes the average wage in city c by one unit when the wage spillover mechanism is at work. To see this more clearly, the effects conventionally associated with shifts in industrial composition on average wages in a city can be written as $A_{ct} = \sum_j (\Delta\eta_{cjt+1})\varpi_{jt}$ , where the effect of change in industrial composition on wages are neglected. If a shift in local industrial composition of employment does not affect sectoral wages, then $A_{ct}$ measures the total effect of change in industrial composition on average wages. However, if wages are instead determined according to equation (4), then I must include the impact of changes in local compositions on local wages. In this case, the total effect becomes $A_{ct} + \frac{\gamma_{c2}}{(1-\gamma_{c2})}\Delta R_{ct}$ . Given the decomposition of the change in the measure of industrial composition I have used, the total effect can be written as:

$$A_{ct} + \frac{\gamma_{c2}}{(1-\gamma_{c2})}\Delta R_{ct} = A_{ct} + \frac{\gamma_{c2}}{(1-\gamma_{c2})}\left(\sum_j (\Delta\eta_{cjt+1})\varpi_{jt} + \sum_i \eta_{cjt+1}(\Delta\varpi_{jt+1})\right)$$

$$= A_{ct} + \frac{\gamma_{c2}}{(1-\gamma_{c2})}\cdot\left(A_{ct} + \sum_i \eta_{cjt+1}(\Delta\varpi_{jt+1})\right)$$

$$= \left(1 + \frac{\gamma_{c2}}{1-\gamma_{c2}}\right)A_{ct} + \frac{\gamma_{c2}}{(1-\gamma_{c2})}\sum_i \eta_{cjt+1}(\Delta\varpi_{jt+1})$$

Thus, in the case where sectoral wage premia are constant over time, the total effect becomes $\left(1 + \frac{\gamma_{c2}}{1-\gamma_{c2}}\right)A_{ct}$, in which case $\frac{\gamma_{c2}}{1-\gamma_{c2}}$ measures the magnitudes of order by which the general equilibrium effect is greater than the conventional effects associated with shifts in local industrial compositions.[19]

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[19] As explained in section two under equation (1), $1/(1-\gamma_{c2}) = 1 + \gamma_{c2}/(1-\gamma_{c2})$ is the total wage impact of a change in industrial composition that changes the average wage in city *c* by one unit when the wage spillover mechanism is at work. The conventional measure of such an impact disregards the further changes in wages caused by the initial change in average wage resulting from the shift in industrial composition, which is captured by $\gamma_{c2}/(1-\gamma_{c2})$. In other words, 1 in $1 + \gamma_{c2}/(1-\gamma_{c2})$ is the total conventional impact of the mentioned change in industrial composition and $\gamma_{c2}/(1-\gamma_{c2})$ is the total impact of further changes in wages resulted by the initial change in the average wage in city *c* (i.e., by initial change in industrial composition). Therefore, $(\gamma_2/1-\gamma_2)$, which is the average of $\gamma_{c2}/(1-\gamma_{c2})$ across all cities, captures the magnitudes of order by which the general equilibrium impact is larger than the conventional measure of the effect of a shift in industrial composition on wages.

Thus, the coefficient of $\Delta R_c$ in (6) measures the magnitudes of order by which the general equilibrium impact is larger from the conventional accounting measure of changes in employment compositions on average wages in a city.[20] Hence, an estimate of $\beta^{OLS} = 3.8$ measures the general equilibrium impact to be almost four times in magnitude compared to the conventional accounting measure. Considering an example will explain this relationship more clearly. With an estimate of this magnitude, a pure change in sectoral composition[21] that brings about one dollar direct impact on average wages in a city (the accounting measure of the impact of changes in sectoral composition ignoring the spillover effect and the consequent wage changes) will generate waves of general equilibrium effects on city-sectoral wages so that by the time the new steady state establishes, average wages increase by a total of almost five dollars ($\cong 1 + 3.8$), letting the general equilibrium impact to be somewhere around 4 dollars.

The size of this causal relationship could also be interpreted in more realistic terms. During the ten years from 1990 to 2000, city of Tijuana, the largest city of the Mexican state of Baja California situated on the US–Mexico border adjacent to its sister city of San Diego, California, experienced an increase in the measure of industrial composition of about 0.06 units mainly due to the movements of labour force across sectors in favour of the higher paying sectors such as Mining, Transportation and Communication, Real Estate and Business Services, and Manufacturing and in spite of significant movements out of the Financial Services sectors that generates the highest wage premium in Mexico. At the same time, the sectoral wage in Agriculture, Fishing, and Forestry sector in this city, the only sector with a negative wage premia and with the lowest average wages in Mexico, increased by 43 percent. In the absence of the wage spillovers, wages in agriculture in Tijuana would have increased by only about 20 percent ($0.43 - (0.06 \times 3.8) = 0.202$). In the same way, during the same period Agriculture wages in Xalapa (Jalapa), the capital city of the state of Veracruz, east-central Mexico, the city which Jalapeño peppers take their name from, increased by almost 14.4% while the measure of industrial composition increased by 0.07 units. Had the spillover mechanism not been there, my estimates show that agriculture wages would have actually *declined* by some 12.2%. In this case, enormous relocation of labour force into the Real Estate and Business Services was the root

[20] Notice from comparing equations (A11) and (A12) in the appendix that what we are estimating as the coefficient of change in the measure of industrial composition in equation (6) is $(\gamma_2/1 - \gamma_2)$, which is the average of $(\gamma_{c1}/\gamma_1) \times \gamma_{c2}/(1 - \gamma_{c2})$ in (A11) over cities.

[21] Pure in the sense that overall employment does not change.

cause of the spillover of high wages into other sectors. Of course, these all rely on the assumption that OLS estimates do not suffer from selection bias, are consistent, and are not capturing anything other than the impact of our interest.

## 5.2 Correcting for Sample Selection Bias

The first pit-hole that I am going to deal with is the selection bias. In order to address the issue of selection bias, as discussed in section 3.1, following the approach of Dahl (2002) I have to calculate the probabilities of migration. To do so, first the sample is divided into "movers" and "stayers". Movers are individuals who are now living in a city that is not in their state of birth. Stayers are individuals who are living in a city that is part of their state of birth. For movers, I define groups (or "cells") based on some of the attributes of the individuals. Specifically, five age categories, four education categories, two gender groups, and an indigenous dummy are used, which in total generates 80 cells for the movers. For the stayers, as well as these groups, additional categories based on some family status indicators are added. I create 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. In this way, a total of 320 cells are generated for the stayers. The higher number of cells for the stayers is in accordance with their higher share in the sample. $P_{kbc}$ 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, $P_{kbb}$ 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.

After preparing the migration probabilities, I estimate the selection-bias-corrected version of equations (8) and (10) as presented in equations (13) and (14) respectively, and proceed with corrected estimates of national sectoral wage premia and corrected city-sector wage levels as the left-hand-side-variable. The estimation results of the equations (13) and (14), which are not presented here, indicate that the correction terms are highly significant and therefore, it is probable that the previous result actually suffer from the selection bias.

The third and fourth columns in Table (5.2) report the results of OLS estimation of equation (6) after correcting for sample selection bias. The results are very similar to those reported in columns one and two when I had not corrected for the self selection in the sample. Thus, it is to be concluded that the OLS estimates are not contaminated by the existing self selection in the sample. Again, controlling for the changes in city employment rates or city-sector employment rates does not seem to make any difference in the size or significance of the coefficient of the change in the measure of industrial composition.

## 5.3 Dealing with Endogeneity

The next is to address the endogeneity of the regressors. Column IV (1) in table (5.2) reports the results of using the all instruments in group one and two for estimating equation (6) when city level employment rate is controlled for and Column IV (1) in table (5.3) shows the associated first-stage results. The associated joint redundancy F test and p-value in the first stage regression of $\Delta R_c$ are 11.8 and 0.00 respectively, and those associated with the first stage of $\Delta ER_c$ are 7.57 and 0.00 respectively. One should note that with the use of the two groups of instruments, the requirement for validity of the IV approach is increased to the combination of the conditions that were required for each group separately. The results of the second stage are indicative of a highly significant and positive relationship between the city-sector wages and the measure of industrial composition of a magnitude that is not significantly different from the OLS estimates[22]. This is an indication of the fact that under the random walk assumption and the assumption required for validity of group one instruments, it seems to be the case that the stronger condition required for the consistency of OLS is satisfied. In other words, the OLS estimates of the relationship between the change in city-sector wages and the change in the measure of industrial composition is consistent and does not suffer from endogeneity. What is interesting is that even though it seems to be the case that the change in the city level employment rate is endogenous, as the test for exogeneity of this variable strongly rejects the null (see footnote 22 below), it does not affect the OLS estimates of the relationship between wages and the measure of industrial composition as if the change in the measure of industrial composition is orthogonal to the change in employment rate.

Column IV (2) in table (5.2) reports the result of estimating equation (6) while controlling for city-sector employment rates and using as instruments minimum distance from border, its interaction with region, the interactions of region and a full set of industry dummies, IV1, IV2, and the interactions of $IV_{ER}$ with a full set of industry dummies for which the results of the first-

[22] 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. For more information see the help for ivreg2 in STATA. The P-value for the case of the estimates reported under column IV (1) is 0.89 for $\Delta R_c$, is 0.02 for $\Delta ER_c$, and is 0.05 for $\Delta R_c$ and $\Delta ER_c$ jointly. The null hypothesis is that the variable of interest is not endogenous.

stage estimations is reported under column IV (2) in table (5.3). The results of the first and second stage are very similar to the previous case where change in the city level employment rate was the control variable.

The estimation results of equation (6) using the decomposed change in the measure of industrial composition ($\Delta R_{ct} = \Delta R_{ct}^1 + \Delta R_{ct}^2$) are reported in table (5.4) noting that the results are corrected for sample selection bias. In this case the OLS estimates are reported under columns OLS (1) and OLS (2) for the same difference in the control variable as before; under OLS (1) the control variable is change in the city employment rate while under OLS (2) it is the change in city-sector employment rate. Estimates of the relationship between the change in city-sector wages and both parts of the decomposed change in the measure of industrial composition are highly significant and not significantly different from each other and from the OLS results reported under columns OLS (3) and OLS(4) for $\Delta R_c$ in table (5.2), which are corrected for sample selection bias.[23] This is providing evidence for the theoretical expectation that the source of improvement in the outside option of the workers, whether shifts in industrial composition within cities in favour of the higher paying sectors while keeping the wage premia fixed or improvements in the wage premia while keeping the distribution of employment fixed, should not matter. Again, controlling for change in city employment rate versus city-sector employment rate does not make any difference.

Column IV (1) in table (5.4) reports the results of estimation of equation (6) in a decomposed fashion while controlling for the change in city employment rate, using minimum distance from border, region, the interaction of the two, IV1, IV2, and $IV_{ER}$ as instruments for $\Delta R_{ct}^1$, $\Delta R_{ct}^2$, and $\Delta ER_c$. Table (5.5) under column IV (1) reports the results of the associated first-stage regressions. The first stage results look fine. The results of the second stage are suggestive of the equality between the estimates of the coefficients of $\Delta R_{ct}^1$ and $\Delta R_{ct}^2$ and the equality of those with the same coefficients in the OLS estimation of this equation reported under column OLS (1).[24]

[23] Under OLS (1) the P-value for the null hypothesis of having equal estimates for the coefficients of $\Delta R_{ct}^1$ and $\Delta R_{ct}^2$ is 0.54. The P-value for the null hypothesis of having equal estimates of the coefficients on $\Delta R_{ct}^1$ , $\Delta R_{ct}^2$ , and $\Delta R_{ct}$ (under column (3) of table (5.2)) is 0.43. In the same way, under OLS (2) the P-value for the null hypothesis of having equal estimates for the coefficients of $\Delta R_{ct}^1$ and $\Delta R_{ct}^2$ is 0.54, and the P-value for the null hypothesis of having equal estimates of the coefficients on $\Delta R_{ct}^1$ , $\Delta R_{ct}^2$ , and $\Delta R_{ct}$ (under column (4) of table (5.2)) is 0.46.

[24] The P-value for the null hypothesis of having equal IV estimates for the coefficients of $\Delta R_{ct}^1$ and $\Delta R_{ct}^2$ is 0.71, and for the joint exogeneity of these two variables is 0.96.

Column IV (2) in table (5.4) reports the results of estimation of equation (6) in a decomposed fashion while controlling for the change in city-sector employment rate and using minimum distance from border, its interaction with region, the interactions of region and a full set of sector dummies, IV1, IV2, and a full set of interactions of $IV_{ER}$ with industry dummies as instruments for $\Delta R_{ct}^{1}$, $\Delta R_{ct}^{2}$, and $\Delta ER_{c}$. The results of the first and second stages are very much similar with the previous ones under column IV (1).

## 5.4 Robustness

It remains to make sure that the estimates of the impact of measure of industrial composition on city-sector wages are robust to introduction of other existing 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 (Moretti, 2004; Acemoglu and Angrist, 1999), and minimum wages (Fairris, Ropli, and Zepeda, 2008). Additional variables related to these alternative explanations are added to equation (6) to ensure of the robustness of the OLS estimate. The results are shown in table (5.6). As is clear from the results reported in table (5.6), the coefficient of the measure of industrial composition is fairly stable and remains highly significant after the introduction of the new variables one at a time or altogether at once. Among the new controls

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 industries grow faster, as a function of geographic specialization and competition, they find that although specialization has no effect on wage growth, diversity in a city helps wage growth of the industry. Here, following Beaudry et al. (2007) I introduce a measure of "fractionalization" of employment in a city at the start of the decade measured by one minus the Herfindahl index, or one minus the sum of squared sectoral shares in the city. The results are reported under columns OLS (1) and IV (1) in table (5.6). The change in the measure of industrial composition is robust to introducing this alternative explanation for growth in wages at city level. The measure of sectoral diversification appears to be significant (although still with a negative coefficient) both in OLS and after using instruments for $\Delta R_{c}$ and $\Delta ER_{c}$.

Moretti (2004) examines wages in U.S. cities in the 1980s and finds that cities with greater increase in the proportion of workers with a BA or higher education have higher wage gains. Acemoglue and Angrist (1999) find weaker results for the impact of education using average years of education in a state. Because I have already controlled for the level of education in estimating the sectoral wage premia and therefore, our measure of measure of industrial compositions does not reflect cities with higher wages due to having higher levels education. However, I will control for both measures of education discussed in the two studies mentioned above. One measure is the change in the proportion of workers with a BA or higher education and the other is using average years of schooling as an alternative measure of the education level of a city. The results are shown under columns OLS (2) and IV (2) in table (5.6), where I use initial levels of workers with a BA or higher and initial average year of schooling among workers as instruments in addition to the instruments in groups one and two. The change in the measure of industrial composition is robust to introduction of these variables. Neither of the new variables is significant, which is close to the results Acemoglue and Angrist (1999) have.

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. Changes in minimum wages could also affect the bargaining power of workers as an increase in minimum wages improves the outside options. I use the data on minimum wages from Bank of Mexico's Annual Report[25] that provides this information for three broad geographic divisions of the municipalities Mexico and construct proper measure of its changes at city level by matching it with the geographical divisions that I am using in this study (the metropolitan areas). Essentially, I use a number-of-worker weighted average of the minimum wages in the municipalities that form a metropolitan area as the measure of minimum wage at city level and control for the change in this variable over time to capture the idea in Fairris et al. (2008). According to the results reported under columns OLS (3) and IV (3) in table (5.6), estimate of the coefficient of change in the measure of local industrial composition is robust to controlling for the change in minimum wages. The sign of the coefficient of the change in minimum wages is not consistent with expectation, but is not significantly different from zero

[25] Annual Report 2003, Bank De Mexico, Accessed on April 2004, p.139.

in both OLS and IV estimation, where the initial minimum wages is used as the additional instrument.

Finally, the last two columns in table (5.6) under columns OLS (4) and IV (4) report the results of the robustness tests introducing all the alternative explanations discussed above at once to equation (6). The change in the measure of industrial composition seems to be finely robust. What is interesting here is also that the change in average years of schooling is marginally significant at 10%. This variable is measuring the average social return of adding one more year to the average years of schooling in city level in Mexico during the 1990s. The social rate of return to education in terms of percentage increase in wages seems to be at least about 8%.

## 6 Conclusion

Industrial or trade policy changes may result in shifts in industrial compositions that are not necessarily the same in different regions sub-nationally. If there are further effects associated with shifts in industrial compositions, the heterogeneous patterns of local compositional restructurings translate into spatially heterogeneous ultimate local impacts. *What happens to wages when local industrial composition of employment shifts?* Beaudry et al. (2007) address this question in the context of the U.S. cities during 1970-2000 and find substantial general equilibrium wage effects associated with shifts in industrial composition. Here, as an extension of their results to the case of the developing countries, I intend to study wage effects of policy induced shifts in industrial compositions in Mexico.

In this paper, I address the question posed above in the context of Mexican cities during the 1990s, the decade during which NAFTA was enacted. Using Mexican census data, I measure city compositions of sectoral employment, as employment-share weighted sum of national sectoral wage premia, and exploit geographical variation in this measure over time to see whether there are general equilibrium effects associated with shifts in local sectoral compositions that systematically affect local wages across all sectors within cities.

The results indicate significant and substantial within-city general equilibrium wage effects causally associated with local changes in sectoral composition of employment; i.e., controlling for the wage effect of induced changes in city-sector labour demands, cities with higher induced concentration of employment in higher paying sectors tend to have significantly higher growth in wages across all sectors. The magnitude of the general equilibrium wage effects found here is almost 4 times as big as the wage effect conventionally associated with shifts in industrial compositions, which neglects general equilibrium effects. A shift in a city's industrial composition that increases its measure by 0.01 units, would as a result of the general equilibrium effects identified here increase sectoral wages in that city by about 4%, holding the city-sector employment rates (i.e., the demand effect associated with the change in industrial composition) constant. The estimates do not suffer from endogeneity and are robust to correcting for sample selection bias generated by regional migrations within Mexico, and to the introduction of alternative explanatory mechanisms.

It is important to emphasize that the relationship discussed here is about the general equilibrium wage effects that are associated with shifts in the composition of demand for labour rather than changes in overall demand. In fact, in estimating the relationship of interest, I control for the wage effects induced by changes in overall city demand or city-sector demands for workers by including proper employment rates in the right-hand-side of estimation equations.

The findings accentuate the need for policy-analysis approaches that take into account general equilibrium effects and address spatial heterogeneity of policy impacts across regions and localities. It is shown here that in Mexico during the 1990s there were general equilibrium wage effects associated with shifts in local industrial compositions. Further, it is shown that induced shifts in local industrial compositions are not the same in different localities. As a result, while in majority of Mexican cities the induced shifts in local industrial compositions favoured higher paying sectors and substantially improved the earnings of workers during the 1990s, in some cities mostly in South of Mexico, as a result of different pattern of induced local shifts in structure of employment, growth in workers' earnings actually decreased. Such results indicate an increase in the North-South wage gap in Mexico during the 1990s. The findings here may explain the observed growing wag gap in Mexico (Hanson, 2005b; Chiquiar & Hanson, 2007).

# *Appendix*

## *A.1. Theory*

Here, I will reproduce the theoretical model in Beaudry et al. (2007). 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:

$$Y = \left[\sum_{i=1}^{\mathrm{I}} \left(a_i Z_i^{\chi}\right)\right]^{1/\chi}, \quad \chi < 1. \qquad (A1)$$

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:

$$\rho V_{ic}^{f} = (p_i - w_{ic} + \epsilon_{ic}) + \delta\left(V_{ic}^{v} - V_{ic}^{f}\right), \qquad (A2)$$

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:

$$\rho V_{ic}^{v} = \phi_c\left(V_{ic}^{f} - V_{ic}^{v}\right), \qquad (A3)$$

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:

$$\rho U_{ic}^{e} = w_{ic} + \delta(U_{ic}^{u} - U_{ic}^{e}), \qquad (A4)$$

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:

$$\rho U_{ic}^{u} = b + \tau_c + \psi_c\left[\mu U_{ic}^{e} + (1 - \mu)\sum_j \left(\eta_{jc} U_{jc}^{e}\right) - U_{ic}^{u}\right], \qquad (A5)$$

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*. As Beaudry et al. (2007) argue, 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:

$$\left(V_{ic}^{f} - V_{ic}^{v}\right) = \left(U_{ic}^{e} - U_{ic}^{u}\right) \times \kappa\,, \qquad (A6)$$

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:

$$M\big((L_c - E_c), (N_c - E_c)\big),$$

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:

$$\delta ER_c = M\left((1 - ER_c), \left(\frac{N_c}{L_c} - ER_c\right)\right) = (1 - ER_c)^{\sigma} \left(\frac{N_c}{L_c} - ER_c\right)^{1-\sigma}, \qquad (A7)$$

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:

$$c_{ic} = V_{ic}^{v}, \qquad (A8)$$

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 $\Omega_{ic}$:

$$c_{ic} = \frac{N_{ic}}{\Upsilon_i + \Omega_{ic}}.$$

where $\Upsilon_i$ 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:

$$\psi_c = \frac{\delta ER_c}{1 - ER_c} \text{ and } \phi_c = \left(\frac{1 - ER_c}{\delta ER_c}\right)^{\frac{\sigma}{1-\sigma}}. \qquad (A9)$$

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 (A6), (A7), and (A8). 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:

$$w_{ic} = \gamma_{c0} + \gamma_{c1} p_i + \gamma_{c2} \sum_j \eta_{jc} w_{jc} + \gamma_{c1} \epsilon_{ic}, \qquad (A10)$$

where the coefficients are:

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

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

$$\gamma_{c2} = \frac{1}{\left[1 + \frac{\rho}{\psi_c(1-\mu)} + \frac{\rho(\rho + \psi_c + \delta) + \delta\psi_c(1-\mu)}{(\rho + \phi_c + \delta)\psi_c(1-\mu)\kappa}\right] \cdot \left[1 + \frac{\delta}{(\rho + \psi_c)}\right]}.$$

These coefficients are implicitly functions of the employment rate through $\psi_c$ and $\phi_c$.

To make progress toward an estimable relationship and overcome the simultaneity inherent in this equation, equation (A10) can be manipulated and transformed to:

$$w_{ic} = \tilde{d}_{ic} + \frac{\gamma_{c1}}{\gamma_1}\frac{\gamma_{c2}}{(1-\gamma_{c2})}\sum_j \eta_{cj}\left(w_j - w_1\right) + \gamma_{c1}\frac{\gamma_{c2}}{(1-\gamma_{c2})}\sum_j \eta_{cj}\,\epsilon_{jc} + \gamma_{c1}\epsilon_{ic}, \qquad (A11)$$

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, $\tilde{d}_{ic} = d_{ic} - \frac{\gamma_{c1}}{\gamma_1}\frac{\gamma_{c2}}{(1-\gamma_{c2})}\sum_j \eta_{cj}\,\hat{d}_j$ with $d_{ic} = \gamma_{c0}\left[1 + \frac{\gamma_{c2}}{(1-\gamma_{c2})}\right] + \gamma_{c1}p_i + \gamma_{c1}\left[\frac{\gamma_{c2}}{(1-\gamma_{c2})}\right]p_1$, $p_i$ being the price of good *i* that is the product of sector *i*, and $\hat{d}_j = \frac{1}{C}\sum_{c=1}^{C}\gamma_{c1}\left(\epsilon_{jc} - \epsilon_{1c}\right)$ 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. (2007) take a linear approximation of (A11) around the point where cities have identical sectoral composition ($\eta_{ic} = \eta_i = \frac{1}{I}$) 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 $\Delta w_{ci}$:

$$\Delta w_{ic} = \Delta d_i + \frac{\gamma_2}{(1-\gamma_2)}\Delta\sum_j \eta_{cj}\left(w_j - w_1\right) + \gamma_{i5}\Delta ER_c + \Delta\xi_{ic}, \qquad (A12)$$

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 I am interested in estimating the coefficient on the changes in average measure of industrial composition in (A12); $\frac{\gamma_2}{(1-\gamma_2)}$. 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 $A_c = \sum_j \left(\eta_{jct+1} - \eta_{jct}\right)\left(w_{jt} - w_{1t}\right) = \sum_j \left(\eta_{jct+1} - \eta_{jct}\right) v_{jt}$; 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 (A12) or (A10), 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*

As described in the text, I am interested in the condition:[26]

$$\operatorname*{plim}_{C,I\to\infty} \frac{1}{I}\frac{1}{C}\sum_{i=1}^{I}\sum_{c=1}^{C} \Delta R_c \Delta\xi_{ic} = 0, \qquad (A13)$$

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

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

or:

$$\operatorname*{plim}_{C,I\to\infty} \frac{1}{I}\frac{1}{C}\left[\sum_{j=1}^{I}(w_j - w_1)\sum_{c=1}^{C}\Delta\eta_{jc}\sum_{i=1}^{1}\Delta\xi_{ic} + \sum_{j=1}^{I}\Delta(w_j - w_1)\sum_{c=1}^{C}\eta_{jc}\sum_{i=1}^{1}\Delta\xi_{ic}\right]. \qquad (A14)$$

Handling the limiting arguments sequentially[27] and allowing for $C \to \infty$ first, we can analyze the two parts of (A14) separately. The first is:

[26] Throughout this section of the appendix the *t* subscript is omitted for simplicity.
[27] Following the approach discussed in Beaudry et al. (2007).

$$\operatorname*{plim}_{C\to\infty}\frac{1}{C}\sum_{c=1}^{C}\Delta\eta_{jc}\sum_{i=1}^{1}\Delta\xi_{ic}. \qquad (A15)$$

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

$$\eta_{ic} \approx \frac{1}{I} + \pi_1\left(\epsilon_{ic} - \frac{1}{I}\sum\nolimits_j \epsilon_{jc}\right) + \pi_2\left(p_i\Omega_{ic} - \frac{1}{I}\sum\nolimits_j p_j\Omega_{jc}\right), \qquad (A16)$$

$$\begin{aligned}
\Delta\eta_{jc} &= \pi_1\left(\Delta\epsilon_{jc} - \frac{1}{I}\Delta\sum\nolimits_j \epsilon_{jc}\right) + \pi_2\left(\Delta p_j\Omega_{jc} - \frac{1}{I}\Delta\sum\nolimits_j p_j\Omega_{jc}\right) \\
&= \pi_1\left[\Delta\left(\hat{\epsilon}_c + \upsilon_{cj}^{\epsilon}\right) - \frac{1}{I}\Delta\sum\nolimits_j\left(\hat{\epsilon}_c + \upsilon_{cj}^{\epsilon}\right)\right] + \pi_2\left(\Delta p_j\Omega_{jc} - \frac{1}{I}\Delta\sum\nolimits_j p_j\Omega_{jc}\right) \\
&= \pi_1\left(\Delta\hat{\epsilon}_c + \Delta\upsilon_{cj}^{\epsilon} - \Delta\hat{\epsilon}_c\right) + \pi_2\left(\Delta p_j\Omega_{jc} - \frac{1}{I}\Delta\sum\nolimits_j p_j\Omega_{jc}\right) \\
&= \pi_1\Delta\upsilon_{cj}^{\epsilon} + \pi_2\left(\Delta p_j\Omega_{jc} - \Delta\overline{p\Omega}_c\right). \qquad (A17)
\end{aligned}$$

Also, since $\Delta\xi_{ic} = \gamma_1\Delta\epsilon_{ic} + \gamma_1\frac{\gamma_2}{1-\gamma_2}\sum_j\frac{1}{I}\Delta\epsilon_{jc}$:

$$\begin{aligned}
\sum_i \Delta\xi_{ic} &= \sum_i\left(\gamma_1\Delta(\hat{\epsilon}_c + \upsilon_{ci}^{\epsilon}) + \gamma_1\frac{\gamma_2}{1-\gamma_2}\frac{1}{I}\sum\nolimits_j \Delta\left(\hat{\epsilon}_c + \upsilon_{cj}^{\epsilon}\right)\right) \\
&= \sum_i\left(\gamma_1\Delta(\hat{\epsilon}_c + \upsilon_{ci}^{\epsilon}) + \gamma_1\frac{\gamma_2}{1-\gamma_2}\Delta\hat{\epsilon}_c\right) \\
&= I\gamma_1\Delta\hat{\epsilon}_c + I\gamma_1\frac{\gamma_2}{1-\gamma_2}\Delta\hat{\epsilon}_c \\
&= I\left(\gamma_1 + \gamma_1\frac{\gamma_2}{1-\gamma_2}\right)\Delta\hat{\epsilon}_c. \qquad (A18)
\end{aligned}$$

Then, given that $E(\Delta\hat{\epsilon}_c) = 0$ (again, recalling that I have removed economy-wide trends) and if $\Delta\hat{\epsilon}_c$ is independent of $\Delta\upsilon_{ic}^{\epsilon}$ and $\Delta p_j\Omega_{jc} - \Delta\overline{p\Omega}_c$, it is straight forward to show that (A15) equals zero.

The second component is:

$$p\lim_{C\to\infty}\frac{1}{C}\sum_{c=1}^{C}\eta_{jc}\sum_{i=1}^{1}\Delta\xi_{ic}, \qquad (A19)$$

where $\sum_{i=1}^{1}\Delta\xi_{ic}$ is again given by (A18), while $\eta_{jc}$ is given by equation (A16) in the text. For (A19) to be zero it is required in addition that $\Delta\hat{\epsilon}_c$ be independent of past values of $\upsilon_{ic}^{\epsilon}$ and of $p_j\Omega_{jc} - \overline{p\Omega}_c$. ***Thus, if $\Delta\hat{\epsilon}_c$ is independent of the past and is independent of $\Delta\upsilon_{ic}^{\epsilon}$ and of $\Delta p_j\Omega_{jc} - \Delta\overline{p\Omega}_c$, then (H1) equals zero and OLS is consistent.***

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

$$\operatorname*{plim}_{C,I\to\infty}\frac{1}{I}\frac{1}{C}\sum_{i=1}^{I}\sum_{c=1}^{C}Z_c\Delta\xi_{ic} = 0, \qquad (A20)$$

for what I call IV1:

$$Z_c = \sum_j \frac{\eta_{jc}(g_{jc}+1)}{\sum_i \eta_{ic}(g_{ic}+1)}(w_j - w_1),$$

where $g_{ic}$ is the growth rate in employment in industry $i$, city $c$. Given this, first allowing for $C\to\infty$, the left hand side in (H7) becomes:

$$\operatorname*{plim}_{C\to\infty}\frac{1}{C}\sum_j (w_j - w_1)\sum_{c=1}^{C}\frac{\eta_{jc}(g_{jc}+1)}{\sum_i \eta_{ic}(g_{ic}+1)}\sum_{i=1}^{I}\Delta\xi_{ic}. \qquad (A21)$$

Thus, (A21) equals zero under the same conditions under which (A19) equals zero (that $E(\Delta\hat{\epsilon}_c) = 0$ and $\Delta\hat{\epsilon}_c$ is independent of the past values of $\upsilon_{ic}^{\epsilon}$ and $p_j \Omega_{jc} - \overline{p\Omega_c}$), given that $g_{jc}$ is a function of minimum distance from U.S. border which is expected to be orthogonal to $\Delta\hat{\epsilon}_c$ . Obviously this condition will be satisfied if $\hat{\epsilon}_c$ behaves as a random walk with increments independent of the past.

Similarly, the relevant condition when using IV2 is given by:

$$\operatorname*{plim}_{C\to\infty} \frac{1}{C} \sum_{j} \Delta(w_j - w_1) \sum_{c=1}^{C} \eta_{jc} \left(g_{jc} + 1\right) \sum_{i=1}^{I} \Delta\xi_{ic} = 0, \qquad (A22)$$

which is satisfied under the same conditions required for (A21) to equal to zero.

OLS can provide consistent estimates and for it to do so requires the assumptions needed for the IV's to provide consistent estimates (that changes in the absolute advantages for a city are independent of the initial set of comparative advantage factors for that city) plus the stronger assumption that changes in absolute advantage and changes in comparative advantage are independent. Thus, if OLS and IV estimates are equal then this is a test of the stronger assumption about independence in changes assuming the instruments are valid.

## *A.3. DATA*

In the original database the sample universe is composed of de jure Mexican citizens, including Mexican diplomats and their families residing in foreign countries and foreign residents of Mexico. The census sought to enumerate vagrants, the homeless, and the transient workers and excludes persons living abroad or in group quarters (buildings used to shelter people for reasons of assistance, health, education, religion, confinement, or service). Field work duration for the 1990 census was March 12-16 and for 2000 census was February 7-18 with enumeration unit being an occupied dwelling and respondent being the householder.

The design of the 1990 census is a systemic sample of dwellings geographically sorted by population size (municipality of locality) and sampling executed independently for each federal unity. Dwellings are the sample units, with sample fraction of 10% or sample size of 8,118,242 persons. The design of the 2000 census is a stratified cluster design; stratified geographically by municipality and urban area and clustered by enumeration areas, blocks of dwellings or localities where all dwellings within a cluster are included in the sample. Sample fraction in 2000 census depends upon demographic heterogeneity of municipalities. The sample was designed to yield representative statistics for all localities with 50,000 or more inhabitants. The data includes weights computed by the census agency that should be used for most types of analysis. Households and individuals are distinguishable in the microdata.

In 2004, a joint effort between CONAPO (Consejo Nacional de Pablocíón), INEGI (Instituto Nacional de Estadística, Geografía, e Informática) and the Ministry of Social Development (Secretaría de Dessarollo Social or SEDESOL) defines the metropolitan areas as:[28]

- 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. The list of the states with their corresponding numerical codes matching the map of the metropolitan areas is presented in table (4.2).

[28] See http://en.wikipedia.org/wiki/Metropolitan_areas_of_Mexico#cite_note-CONAPO-0 cited on October 08, 2008.

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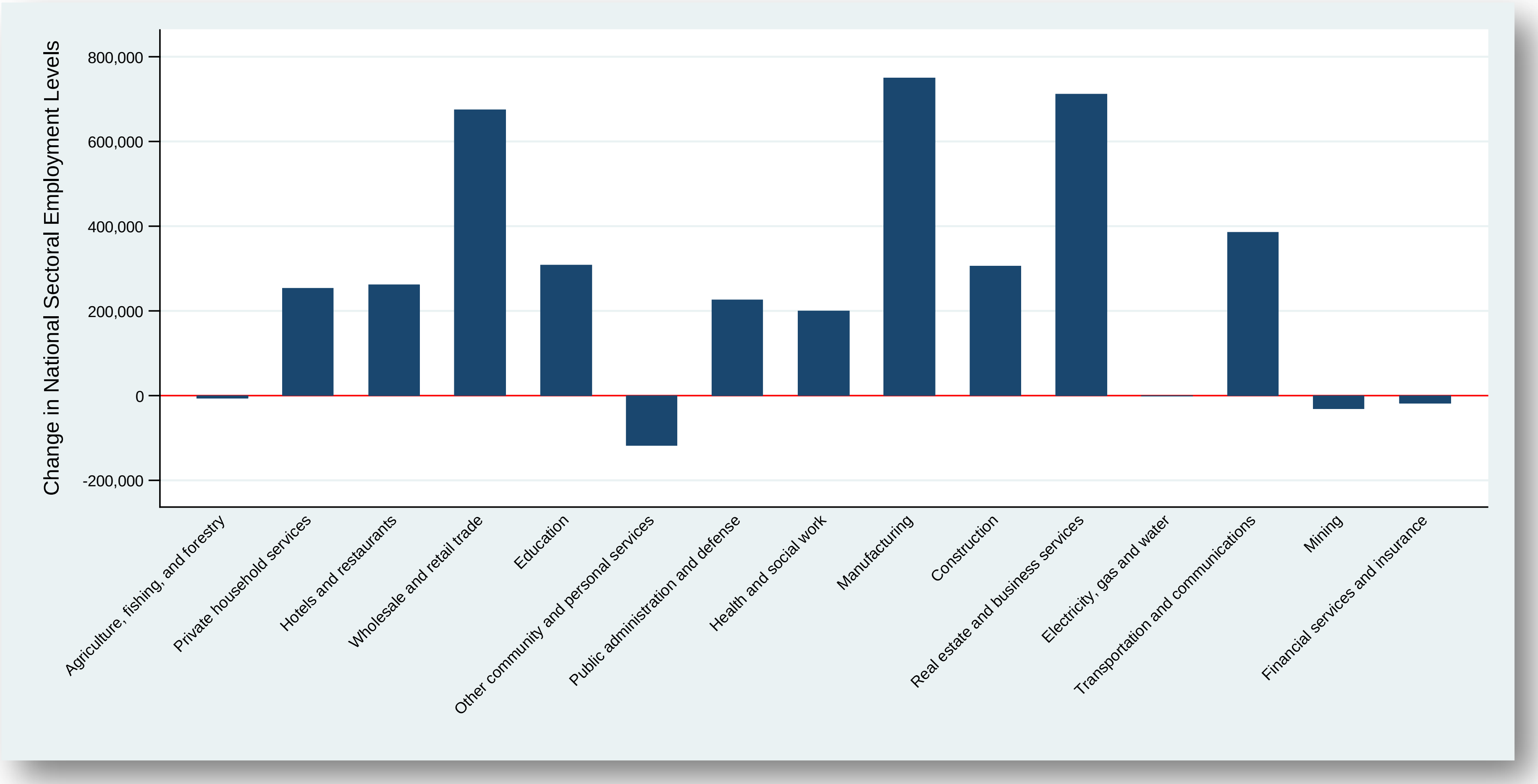
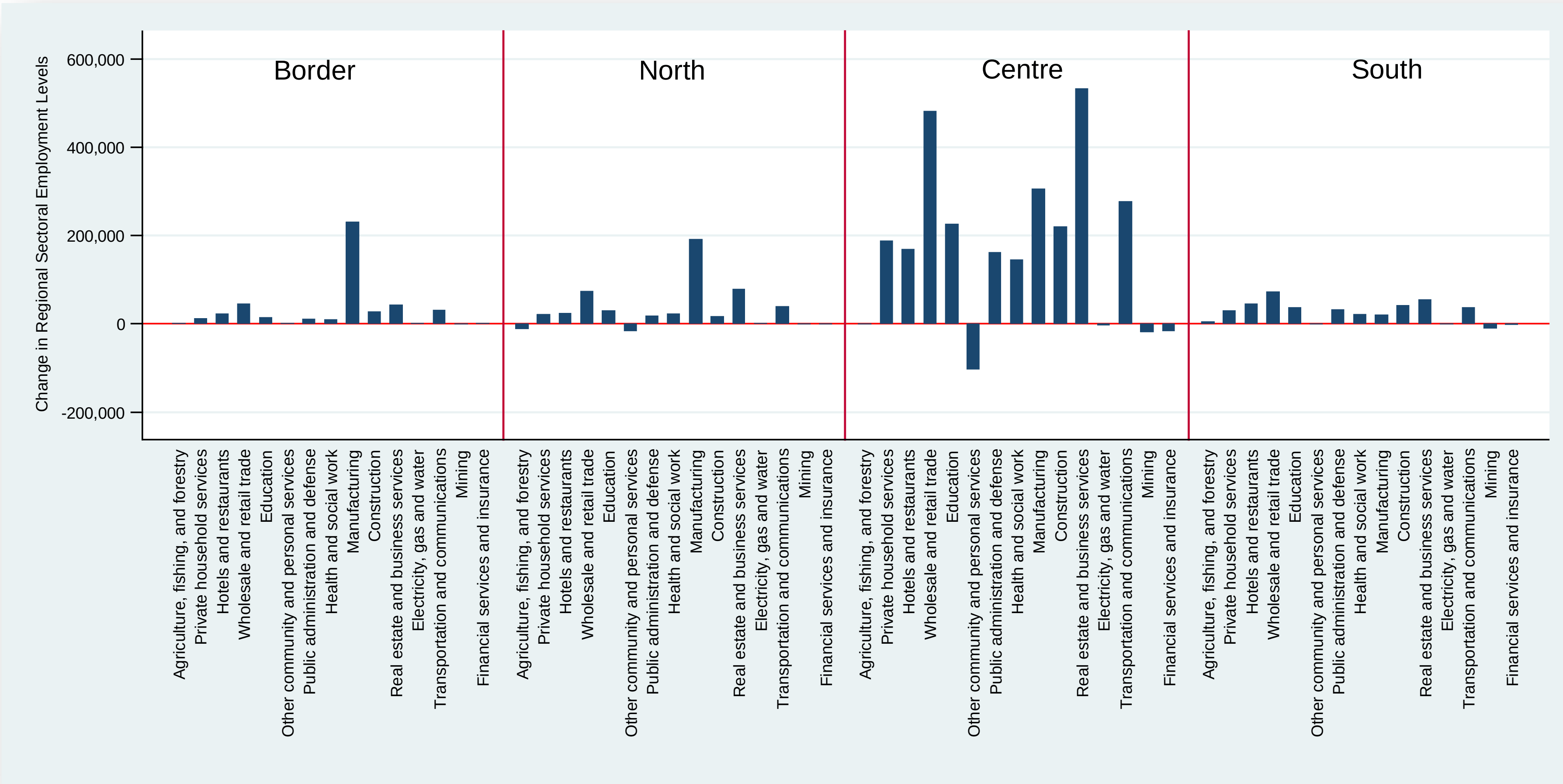
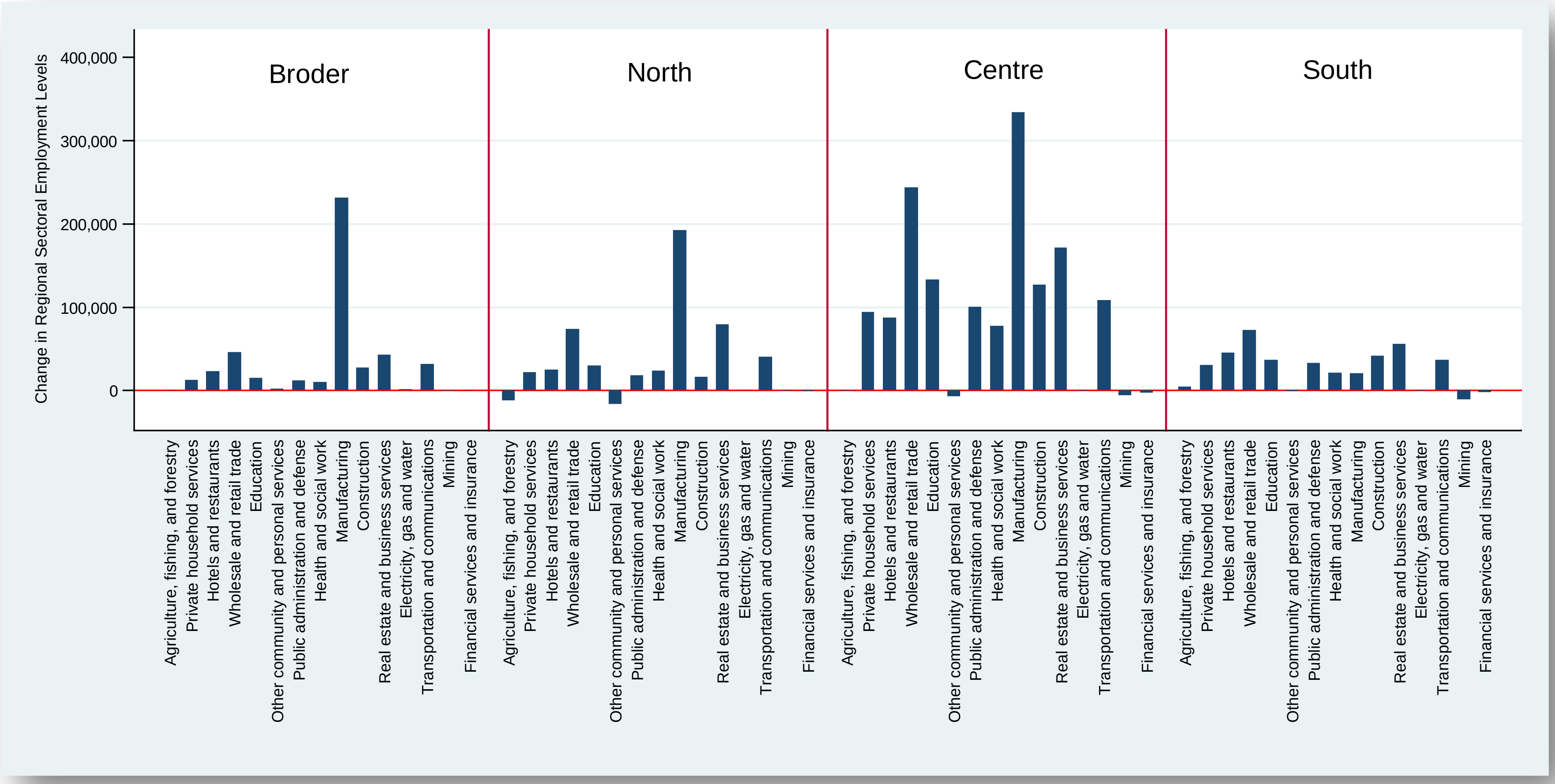
**Graph (1.1) – Change in National Sectoral Employment Levels during 1990-2000 (Sorted according to the national sectoral wage premia increasing from left to right)**



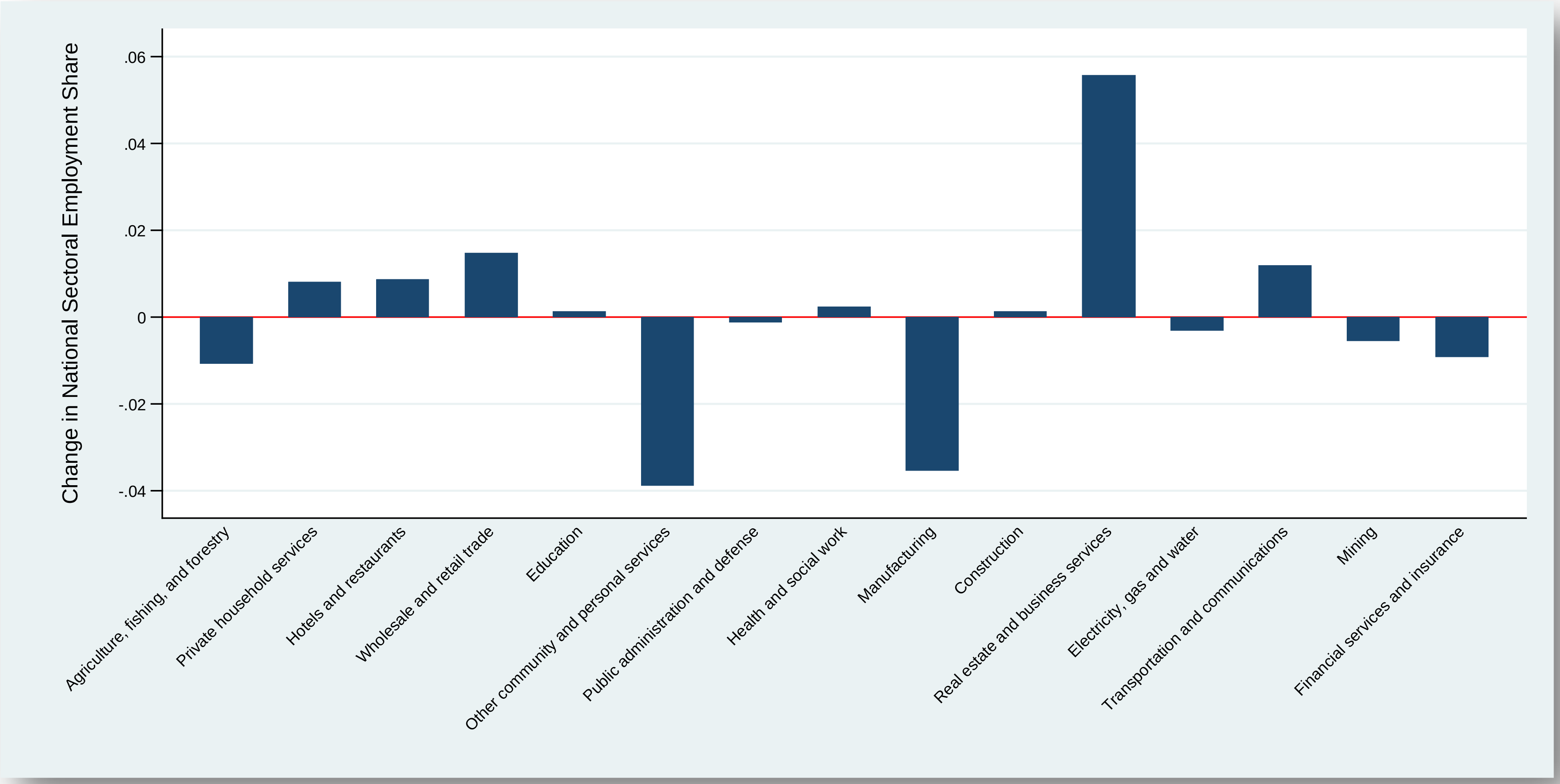
**Graph (1.2) – Change in Regional Sectoral Employment Levels during 1990-2000 (Sorted according to the national sectoral wage premia increasing from left to right within regions)**



**Graph (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)**



**Graph (1.4) – Change in National Sectoral Employment Shares during 1990-2000 (Sorted according to the national sectoral wage premia increasing from left to right)**



**Graph (1.5) – Change in National Sectoral Employment Shares during 1990-2000 (Sorted according to the national sectoral wage premia increasing from left to right within regions)**

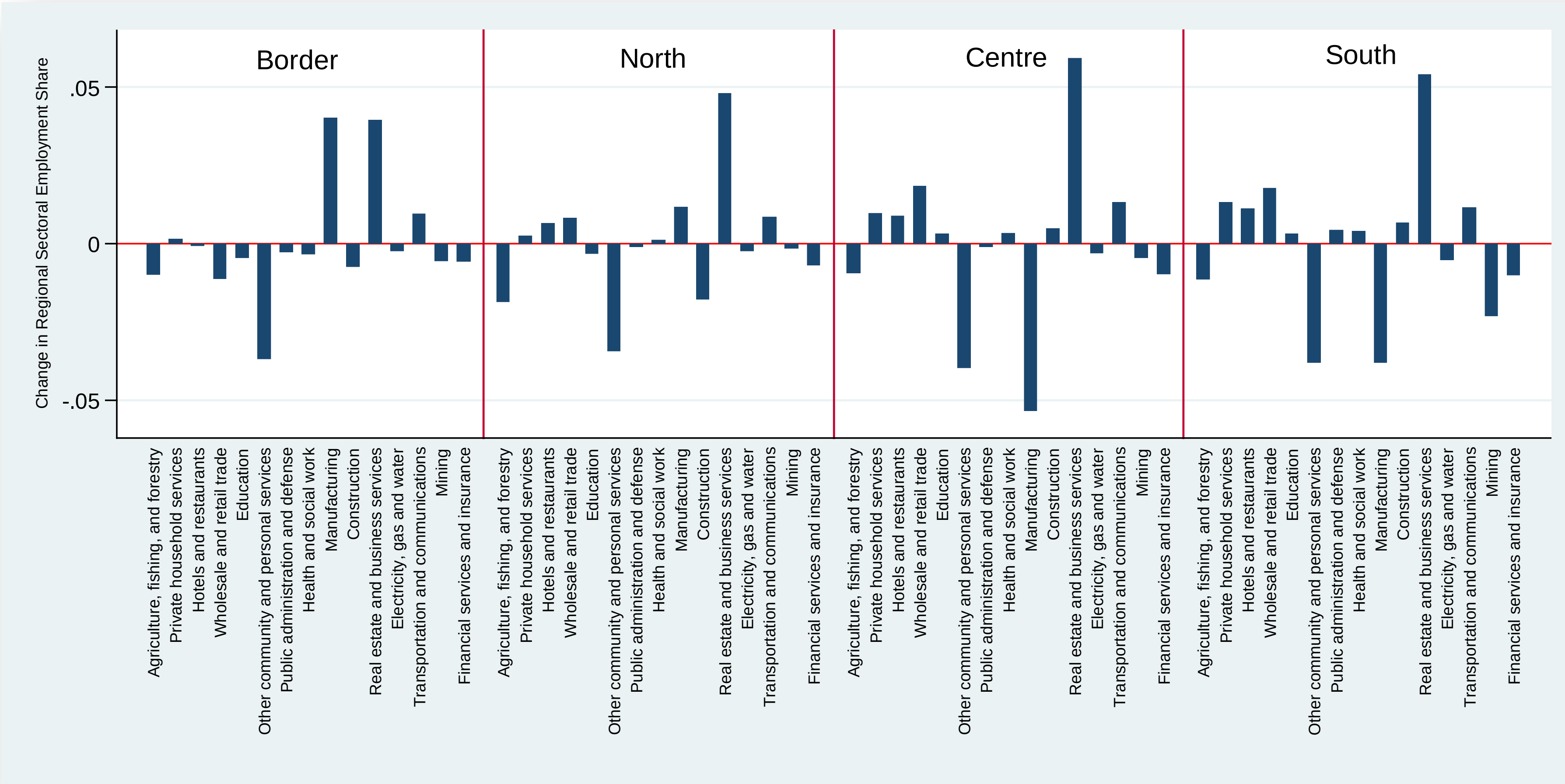


**Table (4.1) – Summary of Sample Statistics**

| | Female 1990 | Male 1990 | Whole Sample 1990 | Female 2000 | Male 2000 | Whole Sample 2000 |
|---|---|---|---|---|---|---|
| **Size of Sample** | 270,116 | 608,676 | **878,792** | 329,278 | 617,820 | **947,098** |
| **Average Age** (years) | 29.7 | 32.4 | **31.6** | 31.8 | 33.1 | **32.6** |
| **Average Years of Schooling** (%): | | | | | | |
| 0 to 1 [No/Little] | 23.6 | 76.4 | **6.4** | 30.0 | 70.0 | **3.3** |
| 2 to 5 [Some Primary] | 21.9 | 78.1 | **12.0** | 28.6 | 71.4 | **8.9** |
| 6 to 8 [Completed Primary] | 26.7 | 73.3 | **28.5** | 29.7 | 70.3 | **22.5** |
| 9 to 11 [Some Secondary] | 37.4 | 62.6 | **32.1** | 31.5 | 68.5 | **30.7** |
| 12 to 13 [Completed Secondary] | 32.1 | 67.9 | **7.5** | 45.0 | 55.0 | **16.6** |
| 14 to 15 [Some University] | 36.9 | 63.1 | **3.1** | 39.5 | 60.5 | **3.4** |
| 16 or More [University Degree] | 33.3 | 66.7 | **10.4** | 41.6 | 58.4 | **14.6** |
| **Average Experience** (years) | 14.9 | 18.3 | **17.2** | 15.7 | 17.9 | **17.1** |
| **Average Monthly Hours Worked** | 41.8 | 47.1 | **45.5** | 43.2 | 50.6 | **48.0** |
| **Average Monthly Income** | | | | | | |
| Constant Year 2000 Peso* | 4,016 | 4,927 | **4,647** | 3,280 | 4,026 | **3,767** |
| (US $) | (425) | (521) | **(491)** | (347) | (426) | **(398)** |
| **Regional** ** **Population** (%): | | | | | | |
| Capital | 32.0 | 68.0 | **41.9** | 36.3 | 63.7 | **41.4** |
| Centre | 29.4 | 70.6 | **26.6** | 33.6 | 66.4 | **28.6** |
| Border | 30.3 | 69.7 | **20.5** | 33.6 | 66.4 | **18.6** |
| North | 30.0 | 70.0 | **5.0** | 35.6 | 64.4 | **4.5** |
| Yucatan | 29.2 | 70.8 | **3.2** | 32.8 | 67.2 | **4.0** |
| South | 31.8 | 68.2 | **2.7** | 33.6 | 66.4 | **3.0** |
| **Average Percentage of Domestic Migrant** (% - State or Higher Level) | 7.39 | 7.59 | **7.47** | 6.13 | 6.63 | **6.41** |
| **Employment Share** (%): | | | | | | |
| Manufacturing | 24.7 | 75.3 | **30.7** | 29.1 | 70.9 | **26.4** |
| Wholesale and Retail Trade | 34.5 | 65.5 | **12.5** | 36.0 | 64.0 | **13.6** |
| Other Community and Personal Services | 22.0 | 78.0 | **9.5** | 19.3 | 80.7 | **5.5** |
| Education | 60.5 | 39.5 | **7.5** | 62.2 | 37.8 | **7.6** |
| Construction | 4.2 | 95.8 | **7.4** | 4.6 | 95.4 | **7.8** |
| Public Administration and Defence | 30.3 | 69.7 | **6.2** | 35.1 | 64.9 | **6.1** |
| Transportation and Communication | 12.4 | 87.6 | **6.0** | 14.9 | 85.1 | **7.2** |
| Health and Social Work | 63.8 | 36.2 | **4.4** | 66.9 | 33.1 | **4.6** |
| Hotels and Restaurants | 41.7 | 58.3 | **3.9** | 43.1 | 56.9 | **4.5** |
| Private Household Services | 85.9 | 14.1 | **3.9** | 89.2 | 10.8 | **5.1** |
| Agriculture, Fishing, and Forestry | 5.2 | 94.8 | **3.3** | 7.3 | 92.7 | **3.0** |
| Financial Services and Insurance | 39.8 | 60.2 | **2.5** | 44.1 | 55.9 | **1.6** |
| Mining | 15.3 | 84.7 | **1.0** | 12.3 | 87.0 | **0.5** |
| Electricity, Gas, and Water | 12.5 | 87.5 | **1.0** | 15.4 | 84.6 | **0.7** |
| Real Estate and Business Services | 41.2 | 58.8 | **0.2** | 37.3 | 62.7 | **5.8** |

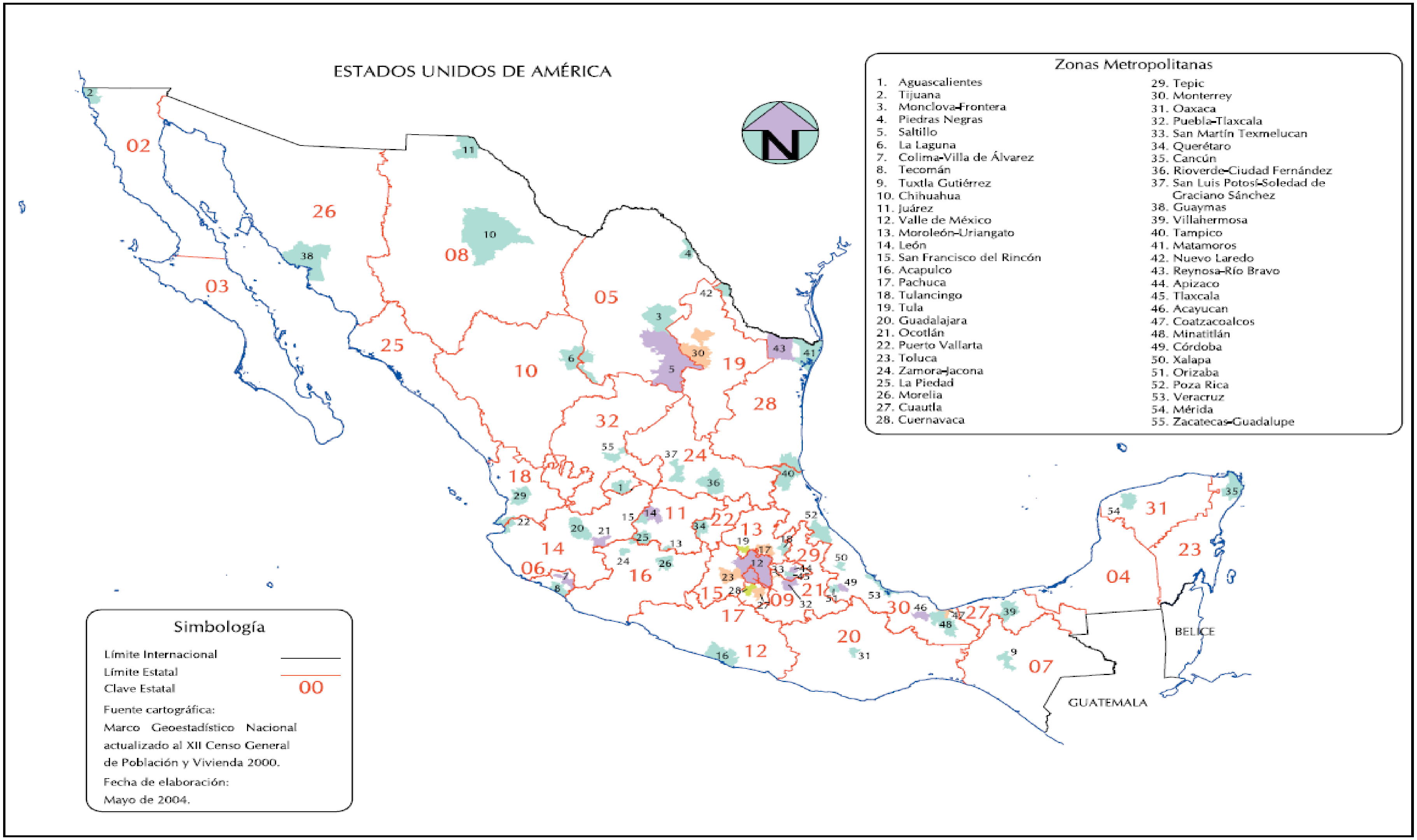
* $1 US = 9.46 Peso (monthly average in year 2000 - source: IFS)

** Border States: Baja California, Chihuahua, Coahuila, Nuevo Leon, Sonora, Tamaulipas
Capital States: Federal District, Mexico
Center States: Colima, Guanajuato, Hidalgo, Jalisco, Michoacan, Morelos, Puebla, Queretaro, Tlaxcala, Veracruz
North States: Aguascalientes, Baja California Sur, Durango, Nayarit, San Luis Potosi, Sinaloa, Zacatecas
South States: Chiapas, Guerrero, Oaxaca
Yucatan States: Campeche, Tabasco, Quintana Roo, Yucatan

**Table (4.2) – Mexican States and Associated Numerical Codes Matching the Map of the Metropolitan Areas**

| Name of State | Numerical Code |
|---|---|
| Aguascalientes | 01 |
| Baja California | 02 |
| Baja California Sur | 03 |
| Campeche | 04 |
| Coahuila | 05 |
| Colima | 06 |
| Chiapas | 07 |
| Chihuahua | 08 |
| Distrito Federal | 09 |
| Durango | 10 |
| Guanajuato | 11 |
| Guerrero | 12 |
| Hidalgo | 13 |
| Jalisco | 14 |
| México | 15 |
| Michoacán | 16 |
| Morelos | 17 |
| Nayarit | 18 |
| Nuevo León | 19 |
| Oaxaca | 20 |
| Puebla | 21 |
| Querétaro | 22 |
| Quintana Roo | 23 |
| San Luis Potosí | 24 |
| Sinaloa | 25 |
| Sonora | 26 |
| Tabasco | 27 |
| Tamaulipas | 28 |
| Tlaxcala | 29 |
| Veracruz | 30 |
| Yucatán | 31 |
| Zacatecas | 32 |

## Figure (4.1) – Mexican Metropolitan Areas




Source: Secretaría de Dessarollo Social, Consejo Nacional de Pablocíón, Instituto Nacional de Estadística, Geografía, e Informática (2004)

**Table (5.1) – Predicting $g_{ci}$**

| | $\Delta ln(e_{ci})$ |
|---|---|
| $mindist_c \times d_{010}$ | -3.9e-04[a]<br>(6.0e-05) |
| $mindist_c \times d_{020}$ | -3.1e-04[n]<br>(1.9e-04) |
| $mindist_c \times d_{030}$ | -1.8e-04[a]<br>(6.6e-5) |
| $mindist_c \times d_{040}$ | -4.3e-04[a]<br>(6.1e-05) |
| $mindist_c \times d_{050}$ | -2.5e-05[n]<br>(5.1e-05) |
| $mindist_c \times d_{060}$ | 5.0e-05[n]<br>(4.9e-05) |
| $mindist_c \times d_{070}$ | 1.1e-04[5]<br>(4.8e-05) |
| $mindist_c \times d_{080}$ | 4.8e-05[n]<br>(5.2e-05) |
| $mindist_c \times d_{090}$ | -5.1e-04[a]<br>(8.7e-05) |
| $mindist_c \times d_{100}$ | 1.9e-06[n]<br>(5.4e-05) |
| $mindist_c \times d_{111}$ | 2.7e-03[a]<br>(2.6e-04) |
| $mindist_c \times d_{112}$ | -2.6e-05[n]<br>(5.5e-05) |
| $mindist_c \times d_{113}$ | 2.3e-05[n]<br>(5.4e-05) |
| $mindist_c \times d_{114}$ | -4.6e-04[a]<br>(7.4e-05) |
| $mindist_c \times d_{120}$ | 1.7e-04[a]<br>(6.2e-05) |
| Obs. | 820 |
| $R^2$ | 0.69 |
| Joint Redundancy Test | F(15,54) = 23.5<br>P-value = 0.00 |

**(.):** Robust, city-clustered standard deviation. **a, n, 5:** Respectively, significance at all of the conventional, none of the conventional, and 5% levels of significance. $d_i$**:** is a dummy variable that is 1 when sector is *i*, and zero otherwise. **010:** Agriculture, Fishing, and Forestry. **020:** Mining. **030:** Manufacturing. **040:** Electricity, Gas, and Water. **050:** Construction. **060:** Wholesale and Retail Trade. **070:** Hotels and Restaurants. **080:** Transportation and Communication. **090:** Financial Services and Insurance. **100:** Public Administration and Defence. **111:** Real Estate and Business Services. **112:** Education. **113:** Health and Social Work. **114:** Other Community and Personal Services. **120:** Private Household Services.

## Table (5.2) – OLS and IV Estimation Results of Equation (6)

| | OLS (1) | OLS (2) | OLS (3) | OLS (4) | IV (1) | IV (2) |
|---|---|---|---|---|---|---|
| $\Delta \boldsymbol{R_c}$ | 3.80[a] (0.60) | 3.78[a] (0.59) | 3.26[a] (0.60) | 3.23[a] (1.20) | 3.65[a] (1.18) | 3.71[a] (1.21) |
| $\Delta \boldsymbol{ER_c}$ | 1.93[n] (1.64) | – | 2.63[n] (1.59) | – | 13.2[a] (4.16) | – |
| $\Delta \boldsymbol{ER_c} \times \boldsymbol{d_i}$ | No | Yes | No | Yes | No | Yes |
| ***Industry Fixed Effects ($d_i$)*** | Yes | Yes | Yes | Yes | Yes | Yes |
| ***Corrected for Sample Selection*** | No | No | Yes | Yes | Yes | Yes |
| ***Instrumented for*** $\Delta \boldsymbol{ER_c} \times \boldsymbol{d_i}$ | No | No | No | No | No | Yes |
| *Obs.* | 820 | 820 | 820 | 820 | 820 | 820 |
| $R^2$ | 0.24 | 0.28 | 0.22 | 0.26 | – | – |
| $\Delta R_c$'s First-Stage Partial $R^2$ ♣ | – | – | – | – | 0.59 | 0.60 |
| $\Delta R_c$'s First-Stage Joint Test for Excl. Instr.♥ | – | – | – | – | F(6,54) = 11.8 P-value = 0.00 | F(34,54) = 14.6 P-value = 0.00 |
| $\Delta ER_c$'s First-Stage Partial $R^2$ ♣ | – | – | – | – | 0.28 | – |
| $\Delta ER_c$'s First-Stage Joint Test for Excl. Instr.♥ | – | – | – | – | F(6,54) = 7.57 P-value = 0.00 | – |
| Over-id Test | – | – | – | – | P-value = 0.19 | P-value = 0.28 |

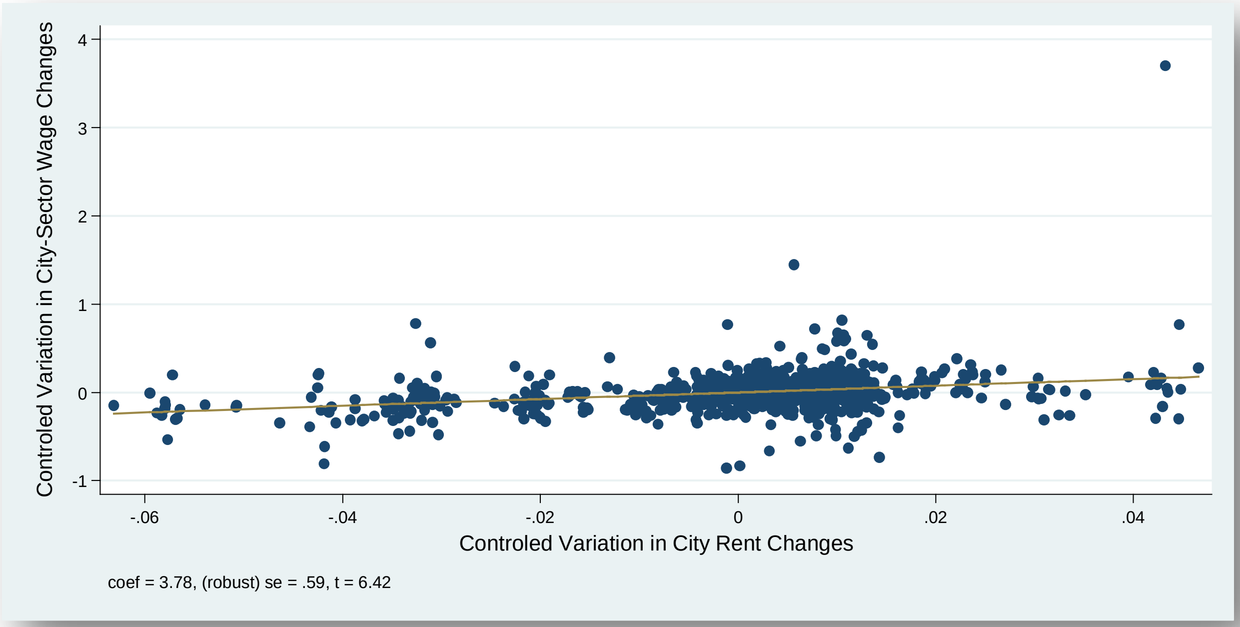
**(.)**: Robust, city-clustered standard deviation. **a, n, 5**: Respectively, significance at all of the conventional, none of the conventional, and 5% levels of significance. **OLS (1) & OLS (3):** OLS estimation results of equation (6) controlling for city employment rates rather than city-sector employment rates. **OLS (2) & OLS (4):** OLS estimation results of equation (6) controlling for city-sector employment rates rather that city employment rates. **IV (1):** IV estimation results associated of the specification under OLS (3) and using IV1 and IV2, and $IV_{ER}$ in addition to minimum distance, region, and the interaction of the two as excluded instruments. **IV (2):** IV estimation results of the specification under OLS (4), using IV1 and IV2, and $IV_{ER} \times d_i$ in addition to minimum distance, its interaction with region, and region $\times$ $d_i$, as excluded instruments. ♣: Squared-partial correlation between excluded instruments and the endogenous variable in the associated first stage regression. ♥: The test is robust to clustering and heteroskedasticity.

**Table (5.3) – First Stage Results Associated with Specifications in Table (5.2)**

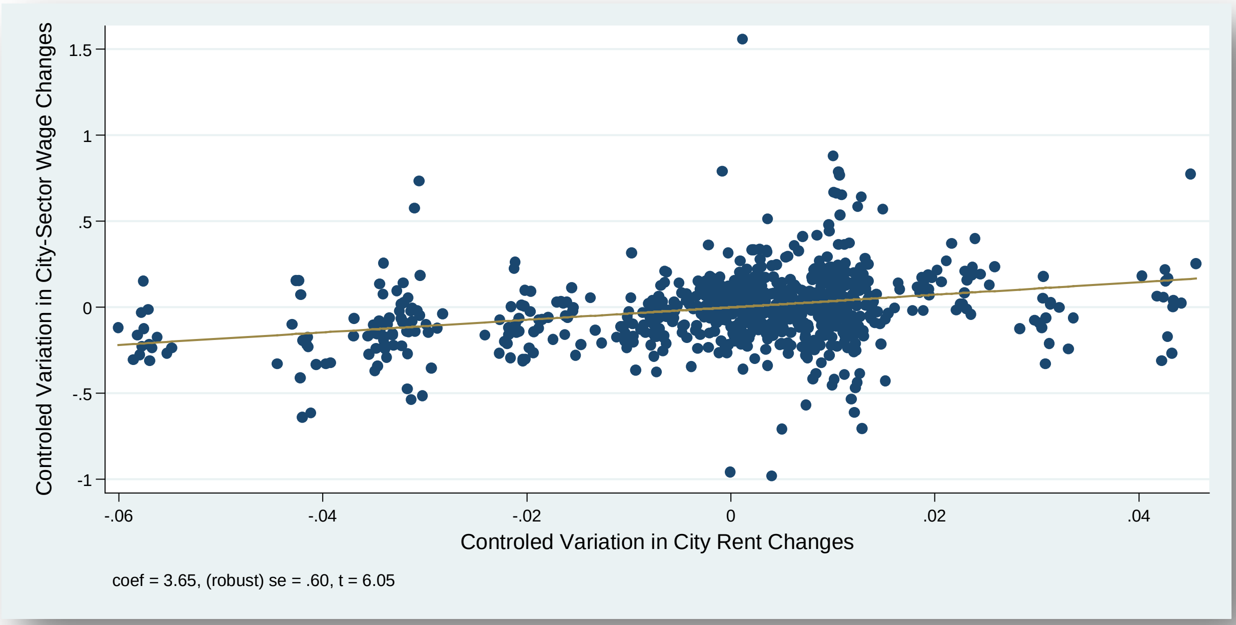
| | IV (1) | | IV (2) |
|---|---|---|---|
| 1st Stage Associated with: | $\Delta R_c$ | $\Delta ER_c$ | $\Delta R_c$ |
| ***Minimum Distance*** | 2.8e-05[10]<br>(1.6e-05) | -2.0e-05[a]<br>(6.5e-06) | 2.7e-05[10]<br>(1.6e-05) |
| ***Region*** | -6.1e-03[n]<br>(4.9e-03) | 2.0e-03[n]<br>(2.0e-03) | – |
| ***Minimum Distance × Region*** | -3.6e-06[n]<br>(5.0e-06) | 2.4e-06[n]<br>(1.6e-06) | -3.4e-06[n]<br>(3.4e-06) |
| ***IV1*** | 1.74[a]<br>(0.56) | -0.08[n]<br>(0.24) | 1.75[a]<br>(0.57) |
| ***IV2*** | 1.25[a]<br>(0.17) | -0.12[n]<br>(0.09) | 1.25[a]<br>(0.18) |
| $IV_{ER}$ | 0.10[5]<br>(0.05) | -0.04[5]<br>(0.02) | – |
| $\boldsymbol{Region \times d_i}$ | No | No | Yes |
| $\boldsymbol{IV_{er} \times d_i}$ | No | No | Yes |
| $\boldsymbol{d_i}$ | Yes | Yes | Yes |
| Partial $R^2$ | 0.59 | 0.28 | 0.60 |
| Joint F-test Statistics | F(6.54) = 11.8<br>P-value = 0.00 | F(6.54) = 7.57<br>P-value = 0.00 | F(34.54) = 14.6<br>P-value = 0.00 |

**(.)**: Robust, city-clustered standard deviation. **a, n, 5, 10**: Respectively, significance at all of the conventional, none of the conventional, 5%, and 10% levels of significance. **IV (1):** 1st stage associated with IV (1) in table (5.2) for the two endogenous variables $\Delta R_c$ and $\Delta ER_c$ when the excluded instruments are minimum distance, region, the interaction of the two, IV1, IV2, and $IV_{ER}$. **IV (2):** 1st stage associated with IV (2) in table (5.2) for the 16 endogenous variables $\Delta R_c$ and $\Delta ER_c \times d_i$ when the excluded instruments are minimum distance, its interaction with region, IV1, IV2, and $IV_{ER} \times d_i$.

**Graph (5.1) – Controlled Variation in Changes in City-Sector Wages vs. Controlled Variation in Changes in the Measure of Local Industrial Compositions**



**Graph (5.2) – Controlled Variation in Changes in City-Sector Wages vs. Controlled Variation in Changes in the Measure of Local Industrial Compositions after Removing the Likely Outlier**



**Graph (5.3) – Controlled Variation in Changes in City-Sector Wages vs. Controlled Variation in Changes in the Measure of Local Industrial Compositions after Removing Both Likely Outliers**

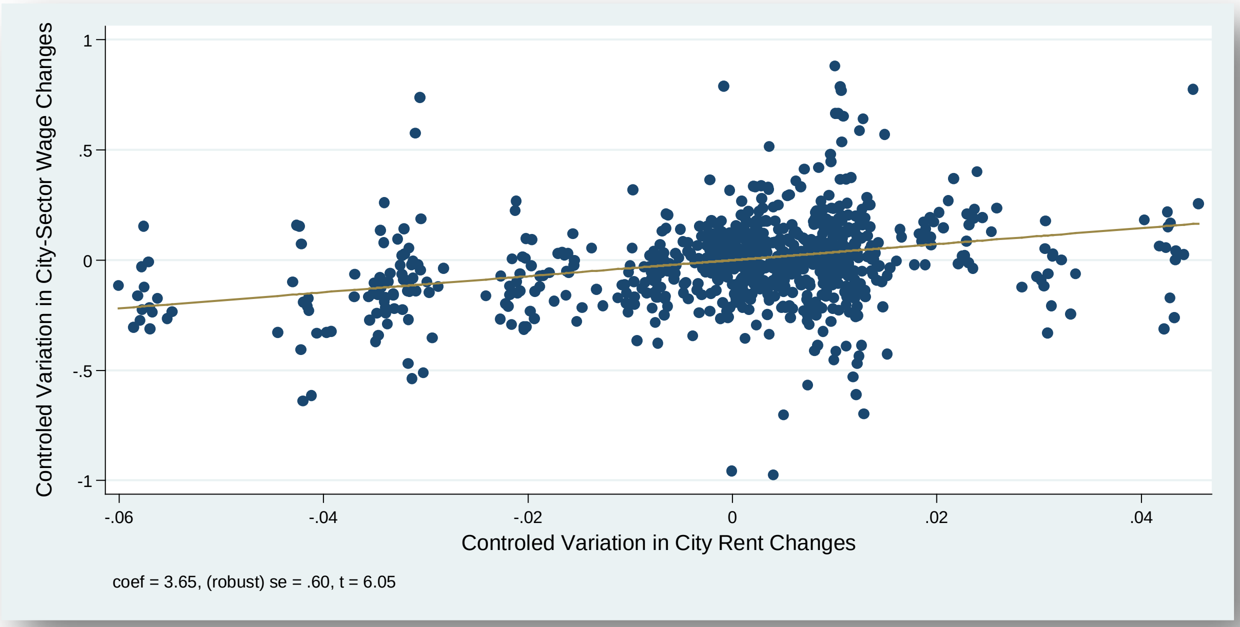


**Table (5.4) – Decomposing $\Delta R_{ct} = \Delta R^1_{ct} + \Delta R^2_{ct}$ ***

| | OLS (1) | OLS (2) | IV (1) | IV (2) |
|---|---|---|---|---|
| $\Delta R^1_{ct} = \sum_i \Delta\eta_{cit+1} v_{it}$ | 3.00[a] (0.83) | 2.93[a] (0.84) | 4.54[5] (1.98) | 4.85[5] (2.17) |
| $\Delta R^2_{ct} = \sum_i \eta_{cit+1} \Delta v_{it+1}$ | 4.08[a] (1.25) | 4.08[a] (1.25) | 3.46[5] (1.61) | 3.39[5] (1.56) |
| $\Delta ER_c$ | 2.64[n] (1.58) | – | 13.6[a] (4.31) | – |
| $\Delta ER_c \times d_i$ | No | Yes | No | Yes |
| ***Industry Fixed Effects ($d_i$)*** | Yes | Yes | Yes | Yes |
| ***Corrected for Sample Selection*** | Yes | Yes | Yes | Yes |
| ***Instrumented for $\Delta ER_c \times d_i$*** | No | No | No | Yes |
| ***Obs.*** | 820 | 820 | 820 | 820 |
| $R^2$ | 0.23 | 0.27 | – | – |
| Partial $R^2$ in $\Delta R^1_{ct}$'s First-Stage♣ | – | – | 0.33 | 0.34 |
| Joint Test for Excl. Instr. in $\Delta R^1_{ct}$'s First-Stage♥ | – | – | F(6,54) = 2.17 P-value = 0.06 | F(34,54) = 3.15 P-value = 0.00 |
| Partial $R^2$ in $\Delta R^2_{ct}$'s First-Stage♣ | – | – | 0.85 | 0.85 |
| Joint Test for Excl. Instr. in $\Delta R^2_{ct}$'s First-Stage♥ | – | – | F(6,54) = 105 P-value = 0.00 | F(34,54) = 173 P-value = 0.00 |
| Partial $R^2$ in $\Delta ER_c$'s First-Stage♣ | – | – | 0.28 | – |
| Joint Test for Excl. Instr. in $\Delta ER_c$'s First-Stage♥ | – | – | F(6,54) = 7.57 P-value = 0.00 | – |
| Over-id Test | – | – | P-value = 0.13 | P-value = 0.25 |
| Test if: Coef. on $\Delta R^1_{ct}$ = Coef. on $\Delta R^2_{ct}$ | P-value = 0.54 | P-value = 0.54 | P-value = 0.71 | P-value = 0.63 |

***** Estimates are corrected for sample selection bias.

**(.):** Robust City-clustered standard deviation. **a**, **n, 5, 10:** Respectively, significance at all of the conventional, none of the conventional, 5%, and 10% levels of significance. **OLS (1):** OLS estimation of equation (6) using the decomposed change in the measure of industrial composition, controlling for city employment rates. **OLS (2):** OLS estimation of equation (6) using the decomposed change in the measure of industrial composition, controlling for city-sector employment rates. **IV (1):** IV estimation of the specification under OLS (1) using IV1, IV2, and $IV_{ER}$ in addition to minimum distance, region, and the interaction of the two as excluded instruments. **IV (2):** IV estimation of the specification under OLS (2) using IV1, IV2, and $IV_{ER}$ in addition to minimum distance, region, and the interaction of the two 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 (5.5) – First Stage Results Associated with Specifications in Table (5.4)**

| | **IV (1)** | | | **IV (2)** | |
|---|---|---|---|---|---|
| 1st Stage Associated with: | $\Delta \boldsymbol{R_c^1}$ | $\Delta \boldsymbol{R_c^2}$ | $\Delta \boldsymbol{ER_c}$ | $\Delta \boldsymbol{R_c^1}$ | $\Delta \boldsymbol{R_c^2}$ |
| ***Minimum Distance*** | 3.3e-05[5]<br>(1.5e-05) | -4.3e-06[n]<br>(6.8e-06) | -2.0e-05[a]<br>(6.5e-06) | 3.3e-05[5]<br>(1.6e-05) | -4.4e-06[n]<br>(6.9e-06) |
| ***Region*** | -0.01[10]<br>(4.1e-03) | 8.2e-04[n]<br>(1.5e-03) | 2.3e-03[n]<br>(2.0e-03) | – | – |
| ***Minimum Distance × Region*** | -4.5e-06[n]<br>(3.1e-06) | 6.6e-07[n]<br>(1.6e-06) | 2.4e-06[n]<br>(1.6e-06) | -4.4e-06[n]<br>(3.2e-06) | 7.2e-07[n]<br>(1.7e-06) |
| ***IV1*** | 1.15[10]<br>(0.58) | 0.44[10]<br>(0.24) | -0.08[n]<br>(0.24) | 1.16[10]<br>(0.59) | 0.44[10]<br>(0.25) |
| ***IV2*** | 0.36[10]<br>(0.20) | 0.81[a]<br>(0.04) | -0.12[n]<br>(0.09) | 0.36[10]<br>(0.20) | 0.81[a]<br>(0.04) |
| $\boldsymbol{IV_{ER}}$ | 0.09[10]<br>(0.05) | 0.01[n]<br>(0.01) | -0.04[5]<br>(0.02) | – | – |
| $\boldsymbol{Region \times d_i}$ | No | No | No | Yes | Yes |
| $\boldsymbol{IV_{ER} \times d_i}$ | No | No | No | Yes | Yes |
| $\boldsymbol{d_i}$ | Yes | Yes | Yes | Yes | Yes |
| Partial $R^2$ | 0.33 | 0.85 | 0.28 | 0.34 | 0.85 |
| Joint F-test Statistics | F(6.54) = 2.17<br>P-value = 0.06 | F(6.54) = 105<br>P-value = 0.00 | F(6.54) = 7.57<br>P-value = 0.00 | F(34.54) = 3.15<br>P-value = 0.00 | F(34.54) = 173<br>P-value = 0.00 |

**(.)**: Robust, city-clustered standard deviation. **a, n, 5, 10**: Respectively, significance at all of the conventional, none of the conventional, 5%, and 10% levels of significance. **IV (1):** 1st stage associated with IV (1) in table (5.4) for the three endogenous variables $\Delta R_c^1$, $\Delta R_c^2$, and $\Delta ER_c$ when the excluded instruments are minimum distance, region, the interaction of the two, IV1, IV2, and $IV_{ER}$. **IV (2):** 1st stage associated with IV (2) in table (5.2) for the 17 endogenous variables $\Delta R_c^1$, $\Delta R_c^2$, and $\Delta ER_c \times d_i$ when the excluded instruments are minimum distance, its interaction with region, IV1, IV2, and $IV_{ER} \times d_i$.

**Table (5.6) – Robustness**

| | OLS (1) | IV (1) | OLS (2) | IV (2) | OLS (3) | IV (3) | OLS (4) | IV (4) |
|---|---|---|---|---|---|---|---|---|
| $\Delta \boldsymbol{R_c}$ | 3.09[a] (0.57) | 3.49[a] (0.88) | 3.21[a] (0.58) | 4.05[a] (1.10) | 3.47[a] (0.58) | 3.92[a] (1.27) | 3.20[a] (0.57) | 3.63[a] (1.16) |
| $\Delta \boldsymbol{ER_c}$ | 1.26[n] (1.78) | 5.46[5] (2.69) | 2.99[10] (1.64) | 11.8[a] (3.85) | 2.37[n] (1.62) | 14.3[a] (4.41) | 1.13[n] (1.90) | 7.95[10] (4.70) |
| ***1 – Herfindahl*** | -0.48[a] (0.19) | -0.41[5] (0.17) | – | – | – | – | -0.51[a] (0.19) | -0.72[a] (0.27) |
| $\Delta \mathbf{BA}+$ | – | – | 3e-08[n] (6e-08) | 4e-08[n] (1e-07) | – | – | -1e-07[n] (10e-08) | 1e-07[n] (2e-07) |
| $\Delta \boldsymbol{Ave.yrs.schl.}$ | – | – | 0.05[n] (0.05) | -0.16[n] (0.17) | – | – | 0.08[10] (0.04) | 0.44[10] (0.22) |
| $\Delta \boldsymbol{Minwage}$ | – | – | – | – | -0.89[n] (0.69) | -0.07[n] (0.92) | -0.99[n] (0.76) | -2.24[n] (1.68) |
| Industry Fixed Effects ($\boldsymbol{d_i}$) | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Obs. | 820 | 820 | 820 | 820 | 820 | 820 | 820 | 820 |
| $R^2$ | 0.25 | – | 0.23 | – | 0.23 | – | 0.26 | – |

**(.)**: Robust city-clustered standard deviation. **a**: Significant at all conventional levels of significance. **n**: Not significant at any conventional level of significance. **5**: Significant at 5%. **10**: Significant at 10%.